**SENSITIVITY OF THE STATISTICAL DOWNSCALING MODEL (SDSM) TO
REANALYSIS PRODUCTS**

A Thesis

Presented to

The Faculty of Graduate Studies

of

The University of Guelph

by

ELENI NINA KOUKIDIS

In partial fulfilment of requirements

for the degree of

Masters of Science

May, 2007

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ISBN: 978-0-494-33879-7

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ISBN: 978-0-494-33879-7

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ABSTRACT

SENSITIVITY OF THE STATISTICAL DOWNSCALING MODEL (SDSM) TO REANALYSIS PRODUCTS

Eleni Nina Koukidis
University of Guelph, 2007

Advisor:
Dr. Aaron A. Berg

To produce accurate daily predictions of future climate variables at the regional scale, the Statistical DownScaling Model (SDSM) identifies relationships between large-scale *predictors* and local-scale *predictands*, using a multiple linear regression model. In this study, separate downscaled precipitation and temperature scenarios were generated using the SDSM with the calibrations and validations derived from two different reanalyses for a climate station in southwestern Ontario. From these comparisons, we have identified statistically significant differences between the two downscaled and observed time-series. Furthermore, the separate downscaled scenarios were used as the climatic inputs into the Soil and Water Assessment Tool (SWAT) hydrologic model to statistically identify significant differences between simulated and observed daily discharge from the Fairchild Creek watershed. These comparisons indicated that the choice of the reanalysis used to calibrate the SDSM can significantly impact the downscaled scenarios used for various hydrologic applications over the region evaluated in southwestern Ontario.

ACKNOWLEDGEMENTS

First, I would like to thank my thesis advisor Aaron Berg for his support, encouragement and most of all patience over the course of my graduate studies. I would also like to thank my research advisor and committee member Jon Warland for his time and valuable comments during the revision process. Additionally, a special thanks to Adam Bonnycastle for always providing me with great technical support.

To my fellow graduate students, I owe thanks to those of you who inspired me throughout many sessions at the grad lounge and other social establishments. Also, I would like to acknowledge the Department of Geography for the supportive research atmosphere they have provided me throughout these last two years.

Finally, to my parents Vera and Petros, and brother Paul, thank you for your continued encouragement and emotional support throughout my entire academic career.

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CHAPTER 1: INTRODUCTION

1.1 Research Background and Context

Over the past century the use of fossil fuels has caused an increase in concentrations of greenhouse gases contributing to an incremental warming of the temperature of the earth. The Intergovernmental Panel on Climate Change (IPCC, 2007) has shown that the global mean annual temperature has increased $0.6\pm0.2^{\circ}\text{C}$ over the past 100 years. From the instrumental record, eleven of the last 12 years (1995-2006) were observed to be the warmest years since 1850. Furthermore, the paleoclimatic record indicated the second half of the 20th century was the warmest 50-year period of the last thousand years (IPCC, 2007). As for future projections for a range of climate models and emission scenarios, the IPCC (2007) stated that the global mean annual temperature is predicted to increase by 0.2°C per decade. As a consequence of these changes, many water resource managers and policy makers are in the process of altering current water policies (i.e. water allocation and use policies) and are planning to reform current water management structures (i.e. dams, reservoirs, levees, etc.) (Sorooshian *et al.*, 2002).

The potential implications of these temperature trends have driven the efforts of climate centers to better understand the future trajectory of the Earth's climate. Recent literature has concluded that General Circulation Models (GCMs) are adequate predictors of global temperature trends and changes in the spatial and temporal distribution of precipitation. However a remaining issue for the utilization of GCM data is the coarse spatial resolution of the predicted output, where they do not account for regional heterogeneity that may affect regional climate (i.e. local topography and convective atmospheric processes) (Mearns *et al.*, 2003; Varis *et al.*, 2004). These regional

processes need to be better resolved for water resource managers and policy makers in southwestern Ontario. This area is one of the most densely populated regions in Canada, home to more than 11 million people, and has been intensively developed agriculturally yielding 30% of Canada's produce (Sanderson, 2004). Additionally, the population and industrial productivity of this region is expected to continue expanding. As a result, it has become increasingly difficult to allocate adequate quantity and quality of water across the domestic, industrial and agricultural sectors in southwestern Ontario (Carter *et al.*, 2005). In preparation for these changes, water resource managers and policy makers are in the process of changing current water policies (i.e. water allocation and use policies), thus requiring accurate future regional climate change predictions (Varis *et al.*, 2004).

To better resolve the coarse spatial scale of GCMs for regional climate forecasting, many techniques have been designed in the past decade to downscale GCM output data to predict future regional climatic variables, such as temperature and precipitation. Although these various techniques will be discussed further in Chapter 2, generally regional climate models (RCMs) and statistical downscaling have emerged within the literature as the most common and suitable approaches for relating large-scale predictor values to regional-scale weather station data. RCMs, the first of the two approaches, simulate climatic variables through a higher resolution climate model nested within a GCM grid to resolve regional processes, such as convective or orographic precipitation, better than the GCM itself (Wilby *et al.*, 1999; Murphy, 1999; Mearns, 2003). While this approach is rapidly evolving, at present RCMs are computationally

demanding, limiting the number of potential experiments and reducing the number of user groups who can make use of this approach.

The second approach is statistical downscaling that relies on empirically based relationships or correlations between local predictands and global-scale predictors (Mearns *et al.*, 2003). Unlike RCMs, the statistical approach has been a popular method of downscaling GCM output data due to its low computational demand and the relatively small number of parameters needed to generate many climate scenarios (Wilby *et al.*, 2000; von Storch *et al.*, 2000; Mearns *et al.*, 2003). The Statistical DownScaling Model (SDSM) has been identified as one of the leading statistical downscaling techniques (Wilby *et al.*, 2002; Dibike and Coulibaly, 2005) and is currently recommended by the Canadian Climate Impacts and Scenarios (CCIS, 2007) as an appropriate downscaling tool. Further, the SDSM is the first downscaling tool offered to the broader, less specialized climate change community (i.e. conservation authorities or private consulting companies). Comparisons between the SDSM and other statistical downscaling methods have demonstrated that the SDSM is a useful downscaling technique capable of reproducing observed climatic variability (Dibike and Coulibaly, 2005; Khan *et al.*, 2006). Recent studies have also assessed the SDSM as a technique to be used for downscaling GCM output for many hydrological applications (Gagnon *et al.* 2005; Diaz-Nieto and Wilby, 2005; Khan *et al.*, 2006).

The SDSM is a hybrid of a stochastic weather generator and a regression-based model where large-scale atmospheric variables are correlated to local-scale variables (Wilby *et al.*, 1999; 2002). The generation of future local-scale climate scenarios from GCM data relies on the pivotal identification of past relationships between local

occurrences and the global-scale atmospheric state using reanalysis data. Two prominent reanalyses commonly in use were developed by the National Center for Environmental Prediction / National Center for Atmospheric Research (NCEP/NCAR) (Kistler *et al.*, 2001) and the European Centre for Medium-range Weather Forecasts (ECMWF) (Uppala *et al.*, 2005). It is known that reanalysis products contain biases which, for the purposes of this study, may impact the development of downscaling scenarios when used with the SDSM. Several studies have compared the NCEP/NCAR and ECMWF reanalyses, indicating that a certain reanalysis outperformed the other in climatological and hydrologic contexts due to their systematic biases (Betts *et al.*, 1998; Annamalai *et al.*, 1999; Roads and Betts, 2000; Trenberth *et al.*, 2001; Berg *et al.*, 2003; Inoue and Matsumoto, 2004). However these biases are typically regional and application specific, therefore neither reanalysis can be identified as the preferred product.

Throughout the SDSM literature the NCEP/NCAR reanalysis has been the only dataset used to represent the past global-scale atmospheric state (Wilby *et al.*, 2002; Diaz-Nieto and Wilby, 2005; Dibiike and Coulibaly, 2005; Gagnon *et al.*, 2005; Khan *et al.*, 2006). Yet, there is still a need to determine if the NCEP/NCAR reanalysis is the most appropriate choice of reanalysis for SDSM calibration when downscaling for certain local-scale variables being used for various applications, such as climatic and hydrologic prediction.

1.2 Research Aim and Objectives

The aim of this research was to evaluate the importance of reanalysis choice in calibrating the SDSM for downscaling daily precipitation and temperature time-series

from GCM output. The strength of two calibrated models (NCEP/NCAR and ECMWF) was assessed through direct comparison between the model errors of the downscaled daily precipitation and temperature to the observed time-series for the Brantford MOE meteorological station in southwestern Ontario. Furthermore, the practical application of these downscaled precipitation and temperature scenarios was assessed in a hydrologic modelling context using the Soil and Water Assessment Tool (SWAT) for the Fairchild watershed within the Grand River Basin in southwestern Ontario. The research objectives necessary to achieve this research aim were:

1. To calibrate and validate the SDSM for the Brantford MOE meteorological station using the ECMWF 40-year and NCEP/NCAR 50-year reanalysis respectively;
2. To downscale daily precipitation and temperature scenarios from four different GCM datasets using the NCEP/NCAR 50-year and ECMWF 40-year reanalysis respectively;
3. To evaluate the downscaled precipitation and temperature errors produced by the two reanalysis calibrated models with respect to observed data;
4. To assess the hydrologic applicability of the downscaled scenarios produced by two reanalysis calibrated models as inputs into the SWAT hydrologic model.

The research undertaken for this thesis is organized as follows: Chapter 2 summarizes the literature pertinent to the undertaken research presented in this thesis in terms of context, methods, applications, and research opportunities. Chapter 3 describes

the detailed research methods used to determine the reanalysis most appropriate for downscaling precipitation and temperature for the Brantford MOE meteorological station in southwestern Ontario. Also described in this section is the hydrologic application of these downscaled scenarios using the SWAT model within the Grand River Basin. The results of these methods undertaken are presented and discussed in Chapter 4 where the main conclusions drawn from these results are summarized in the final chapter.

CHAPTER 2: LITERATURE REVIEW

2.1 Climate Variability and Change

The Intergovernmental Panel on Climate Change (IPCC, 2001) defines climate change as “statistically significant variations of the mean state of the climate or of its variability, typically persisting for decades or longer.” These long-term variations of the climate can be caused either by natural or anthropogenic factors. The Earth’s climate is dynamic and is naturally in a state of change over space and time. Natural mechanisms of climate change have been associated with the greenhouse effect that has for millions of years warmed the Earth, by naturally occurring greenhouse gases (GHG) in the atmosphere that have fluctuated over time. Glacial advancement and retreat cycles have been observed throughout the past and the earth may still be slowly warming from the past glacial period ending approximately 13,000 years ago (Arnell, 2002). Short-term variability of the Earth’s climate is also associated with climate teleconnections between the ocean and atmosphere. The El Nino southwestern Oscillation (ENSO) has been known to cause relatively short-term climatic and atmospheric changes that may distort a long-term climate change signal.

Although climate change can be a natural progression, researchers have noted that over the past 200 years human induced climate change has played a more significant role in climate fluctuation. During these 200 years, a rapid advancement of technology and population growth rate, the atmosphere has experienced a significant increase of GHGs concentrations. The burning of fossil fuels has accelerated and intensified natural climate change at a global and regional scale. This steady increase of GHG emissions into the atmosphere has been to blame throughout the literature for the dramatic climate change

observed over the past 200 years (Douville *et al.*, 2002; Meehl *et al.*, 2004; IPCC, 2007) (Figure 2.1). Figure 2.1 shows that the mean annual temperature over North America has been relatively cooler than the 1961-1990 average and has varied naturally during the past millennia. However, human induced climate change can be clearly illustrated by the dramatic increase of mean annual temperature over the last 200 years.

Figure 2.1 Variations of the surface mean annual temperature of the Northern Hemisphere over the last millennium. Mean annual temperatures (blue and red) and 50-year average (black). The 95% confidence range of the annual data is represented by the grey region (IPCC, 2001).

Although there has been a clear indication that increasing concentrations of GHGs in the atmosphere attributed to human activity, there has also been an increase of aerosol concentrations in the atmosphere observed as well. However, aerosols affect the atmosphere much differently than GHGs. Like GHGs, increasing concentrations of aerosols in the atmosphere can adversely affect the radiation balance that may alter

climate. However, unlike GHGs, Ramanathan *et al.* (2001) and Penner *et al.* (2001) suggest that aerosols have a cooling effect or negative radiation feedback. Aerosols are thought to scatter and absorb incoming solar radiation that could effectively decrease the amount of radiation reaching the earth's surface causing a warming effect. Also aerosol particles act as cloud condensation nuclei (CCN), increasing the potential of cloud cover. An increase of the amount of cloud cover will further increase the albedo of the earth increasing the amount of reflected incoming solar radiation. Furthermore, they suggested that precipitation magnitude and frequency would decrease due to increasing concentrations of aerosols. First, evaporation rates should decrease due to the increased cloud cover reflecting incoming solar radiation (Roderick and Farquar, 2002). Second, aerosols have small radii causing cloud lifetime to be prolonged due to ineffective raindrop coalescence. Nevertheless, aerosols like GHGs can also significantly affect the climate where humans will have to adapt to these changes to physical components, processes and feedbacks of the environment.

Ultimately, the climate is changing and will impact the socio-economic infrastructures of numerous global and regional communities. The next section will briefly illustrate examples of various socio-economic effects that a changing climate will have on the social dynamics of a region, such as southwestern Ontario.

2.1.1. Socio-economic Effects

As climate change alters the physical world, social components must adapt and change as well. A major issue concerning city planners and water managers is the effect of climate changes to the hydrological system. It is suggested that even relatively small

changes in temperature and precipitation has significantly affected, as well as accelerated the hydrologic cycle (Frederick and Major, 1997). Today, the expansion of intensive agricultural practices and the rapid urbanization on urban fringes are increasing the demand for fresh water from either the groundwater reservoirs or surface reservoirs, such as lakes and rivers (Carter *et al.*, 2005). The potential long-term temperature increases and precipitation variation due to climate change are creating the need for new management techniques to maximize efficiency of reservoir storage in the future. Flood protection structures, such as dams, spill ways and levees, may also require new water management techniques due to an increase of flood magnitude and frequency in some areas of the world (Compagnucci *et al.*, 2001; IPCC, 2007). In high latitude and mountainous regions, increasing temperatures are seriously affecting snow and glacial melt processes important to the management of municipal reservoir storage and recharge (Mortsch *et al.*, 2000; Lapp *et al.*, 2005; IPCC 2007). Furthermore, Cohen *et al.* (2001) suggest that a decrease in water level could also negatively affect transportation routes, and thus local economies by, decreasing the available clearance for large cargo ships within the Great Lakes Basin.

In addition to the impacts on water quantity, the quality of fresh water resources is today one of the most pressing social issues around the world. An increase in air temperature, in addition to water level changes, could also affect chemical and biological processes, such as mineral release from soil and bedrock and algal blooms. These effects further re-enforce the need for climate modelling to help predict what is needed to mitigate what may happen in the future.

2.2 Global Climate Modelling

As illustrated in the previous section, climate change will significantly affect the way resources will be managed. A need to better understand how and why the climate was changing sparked an interest within the climate research field to produce models to help answer these questions for resource managers and engineers. However, there still remains significant uncertainty within climate modelling due to the complexity of model design, predicting the future, and scaling issues. An understanding of climate modelling will illustrate why uncertainty exists in predicting future climate change and what can be done to diminish the effects of these uncertainty issues.

2.2.1 General Circulation Models

The topic of climate change has become a major focus in the literature. Research is directed to conceptualize climate models to further understand the interrelated processes and feedbacks between all components of the climatic system. These components can be broken down into the atmosphere, oceans, cryosphere, biosphere, geosphere and arguably the human environment (IPCC, 2001). Over the past 40 years, the introduction and improvement of computational technology has spawned mathematic models attempting to model the climate. As the interest in the study of global climate change increased over the past few decades, many climate centres have designed climate models to be used to predict and forecast future trajectory of climatic variable. These models are more commonly known as general circulation models (GCM) and attempt to predict future climates based on future estimates of GHG and aerosol concentrations and fluxes. The GCM typically divides the components of the climate into a three

dimensional grid having a horizontal resolution of approximately $2.5^{\circ} \times 2.5^{\circ}$, one kilometer vertical resolution, and a potential temporal resolution of 30 minutes. For example, Figure 2.2 illustrates the horizontal resolution of the Canadian GCM2 where climatologic variables are modelled over a $3.75^{\circ} \times 3.75^{\circ}$ grid at a specified vertical level and period of time.

Figure 2.2 Canadian GCM2 $3.75^{\circ} \times 3.75^{\circ}$ Gaussian output grid (CCCma, 2005).

Finally, the GCM requires the estimated GHG and aerosol concentrations to initialize or “force” the model to produce future predicted climatologies, commonly known as a scenario or “storylines”. These scenarios attempt to characterize future GHGs and aerosol emissions based on the rate of population growth, economic growth, technological development, use of fossil fuels and the establishment of social policies such as policies encouraging environmental conservation and sustainable development (IPCC, 2000). In 1992, a scenario widely used by many climate centres, known as the IS92a or “business as usual” scenario, was released by the IPCC in which the atmospheric CO_2 concentration increasing by 1% per year from 1990 to 2100. Presently,

a range representing high, medium and low climate trajectories for future scenario assessment is of more interest to modellers (IPCC, 2001; Mortsch *et al.*, 2005). The IPCC Special Report on Emission Scenarios (SRES) (Table 2.1) attempts to resolve some the uncertainty of the predicting the future by developing a range of possible future outcomes, as well as including GHGs other than CO₂, rather than using a “best guess” scenario. The SRES scenarios are divided into four general categories based on economic, technological and population growth rates as well as social dynamics.

Table 2.1 Special Report on Emission Scenarios (SRES) storylines (IPCC, 2000).

Scenario	Storyline	CO ₂ Emission
A1	<ul style="list-style-type: none"> • Rapid economic growth • Population peaks in 2050 and then declines • Rapid technological growth • Sub-divided into 3 scenarios based on technology <ul style="list-style-type: none"> ○ A1F1 -- fossil fuel intensive ○ A1T -- non-fossil fuel intensive ○ A1B -- balance across all sources 	<ul style="list-style-type: none"> • High (A1F1)
A2	<ul style="list-style-type: none"> • Heterogeneous world, with regional diversity • Self-reliance and preservation of local identity • Continuously increasing global population • Per capita economic growth and technological change are regionally fragmented and slower 	<ul style="list-style-type: none"> • High-medium
B1	<ul style="list-style-type: none"> • Population peaks 2050 and then declines • Rapid changes in economic structures toward a service and information economy • Reductions in material intensity • Emphasis is global solutions to economic, social and environmental sustainability 	<ul style="list-style-type: none"> • Low
B2	<ul style="list-style-type: none"> • Continuously increasing global population although lower than A2 scenario • Intermediate levels of economic development • Less rapid and more diverse technological change than in B1 and A2 scenarios • Emphasis on local solutions to economic, social and environmental sustainability • Environmental protection and social equity at local and regional levels 	<ul style="list-style-type: none"> • Low-Medium

Presently, most modelling centres use the SRES scenarios for climate prediction to understand the possible range of future outcomes. Nevertheless, there is still much uncertainty pertaining to the use of GCMs and scenarios when predicting the future trajectory of the climate that will be further discussed in Section 2.2.3.

2.2 *Reanalysis Projects*

Due to the continual updating and adjusting of global forecasting models and changes of analysis and data assimilation techniques over time, reanalysis products were developed to create continuous time-series that were otherwise unavailable for research of long-term climatic trends (Kalnay, *et al.*, 1996). A reanalysis develops consistent long-term datasets using a "frozen" forecasting weather system to determine if current climate anomalies are significant in comparison to the long-term record (Kalnay, *et al.*, 1996). Figure 2.3 schematically illustrates the data assimilation process used to produce reanalysis products. First, an initial numerical weather forecast model (i.e. GCM) extend observed data obtained from many sources, such as land stations, satellites, buoys, etc., from areas of high data richness to those with lower richness. The output from the forecast model is then combined with observational data and forcing fields as the inputs into an operational weather analysis. The results of this analysis are then used to initialize the next forecast where the process is then repeated for the length of the reanalysis (Gibson *et al.*, 1999).

Figure 2.3 Schematic diagram of data assimilation where every column represents a time-step of the reanalysis (adapted from Gibson *et al.*, 1999).

Two prominent reanalyses commonly in use were developed by the National Center for Environmental Prediction / National Center for Atmospheric Research (NCEP/NCAR) (Kistler *et al.*, 2001) and European Centre for Medium-range Weather Forecasts (ECMWF) (Uppala *et al.*, 2005). The most recent NCEP/NCAR 50-year reanalysis was first preceded by the original 40-year reanalysis initially developed by Kalnay *et al.* (1996) and the ECMWF 40-year reanalysis was also preceded by a 15-year reanalysis initially developed by Gibson *et al.* (1997). Several studies have compared the ECMWF and NCEP/NCAR reanalyses, indicating that a certain reanalysis outperformed the other in climatological and hydrologic contexts due to their systematic biases (Betts *et al.*, 1998; Annamalai *et al.*, 1999; Roads and Betts, 2000; Trenberth *et al.*, 2001; Berg *et al.*, 2003; Inoue and Matsumoto, 2004). However these biases are typically regional and application specific, therefore neither reanalysis can be identified as the preferred product.

2.2.2 Uncertainty

GCMs are considered adequate predictors of global temperature trends, and are continually improving the prediction of the spatial and temporal distribution of

precipitation (Wilby *et al.*, 2004). However, when attempting to utilize GCMs to assess future climate change one must be aware of three major uncertainties. First, although these models are for the most part all designed with the same components, processes and feedbacks, there are major differences between their output data due to parameterization differences of the modellers. The modellers responsible for the parameterization of the different GCMs unconsciously incorporate their own personal biases into the process increasing the uncertainty within the climate models (Shackley *et al.*, 1998; Varis *et al.*, 2004). Each modeller has their own personal understanding, empirical data and views of how to mathematically conceptualize and interrelate the various climate components, processes and feedbacks. An approach to assessing the amount of uncertainty or bias of a GCM parameterization is to force the model with 20th century CO₂ concentrations and comparing the results to historical data (Salathé Jr., 2005). However, the parameters chosen today may not be the same as those chosen under a different climate in the future (Beven, 2001).

Another source of uncertainty in climate change modelling is the choice of climate scenario used to initialize the GCM. Scenarios are riddled with the uncertainty of predicting the future rate of population growth, technologic advancement, economics, and consumption of fossil fuels as well as other natural resources (IPCC, 2000). Even if we were able to accurately predict these factors, we are still unsure of how these changes are converted into GHG and aerosol concentrations (IPCC, 2001). Thus, it is suggested that researchers use more than one GCM and scenario when attempting to model future climate regimes to resolve the possible range of uncertainty (IPCC, 2001; Wilby *et al.*, 2004; Mortsch, *et al.*, 2005). These ranges can be illustrated using in Figure 2.4 where

the possible range of temperature and precipitation change for London, Ontario for the 2050 time period are illustrated (CCIS, 2006). The numerous models and scenarios plotted in Figure 2.4 have created a possible range of temperature change of approximately 5°C and the change in precipitation of approximately 15% at this location. The spread among these models demonstrates the possible uncertainties in both climate modelling and predicting future GHG emissions scenarios. Furthermore, de Loë and Berg (2006) suggest that the uncertainty of GCM output increases as spatial scale decreases as well as at differing temporal scales (i.e. annual, seasonal, daily).

Figure 2.4 Mean trajectory of various GCMs and scenarios centered over southwestern Ontario (CCIS, 2006)

The last and most significant aspect of uncertainty in climate modelling is the coarse spatial resolution of GCM output variables. The spatial resolution of the GCM limits the accuracy of the output data when applied at a regional scale. However, throughout the literature there have been attempts to resolve the spatial uncertainty of GCMs using downscaling techniques. In the next section, several downscaling techniques will be outlined that attempt to resolve the coarse spatial scale of GCMs.

2.3 Downscaling

The coarse spatial resolution of the predicted data produced by GCMs (i.e. 3.75°x 3.75° for Canadian GCM2), simply does not account for regional heterogeneity that may affect regional climate (i.e. lake effects, local topography, and convective atmospheric processes) (Wilby *et al.*, 1999; Murphy, 1999; Mearns, 2003). For example, Figure 2.5 illustrates that the coarse output grid of the CGCM2 does not account for the Great Lakes. The Great Lakes play an important role in the climatology of the surrounding areas due to energy fluxes between the lakes and the atmosphere. Also, GCMs lack the ability to simulate extreme precipitation events because these events are usually dependent on regional processes, such as high intensity rainfall events. Thus, GCMs should only be used as a starting point for research at a local or regional scale, such as municipal water management and planning (Wilby *et al.*, 2000).

To better resolve the coarse spatial scale of GCMs, several techniques have recently been developed by researchers to “scale-down” the coarse GCM output to more accurately forecast climate variation at a local or regional scale. The basic concept of downscaling is relating global scale atmospheric predictors to local scale predictands

Figure 2.5 Canadian GCM2 3.75°x3.75° output grid of North America (CCCma, 2005).

from meteorological weather stations. However, Mearns et al. (2003) suggest that it is not always clear which technique is the most appropriate for the problem in question. The relationships established using a downscaling technique could then be applied to GCM output data to predict climate change at a watershed or municipal scale. Although downscaling resolves the issue of spatial scale, like the GCMs, downscaling techniques can contain biases and uncertainties as well. Also, the GCM data used in the downscaling process could contain biases that would be transferred or magnified through to the local level where the data is used to quantify the local hydrologic parameters (Arnell *et al.* 1996; Gagnon et al., 2005). Thus water resource managers must be aware that downscaled GCM data used for regional hydrologic modelling may contain bias as well (Maurer and Duffy, 2005). This accumulation and transfer of uncertainty throughout the process of predicting climate change from the global to regional scale is commonly known as a cascade of uncertainty (Jones, 2000). It is also suggested that GCM downscaling is not always necessary for certain problems, that only require data resolved at a global scale (Wilby *et al.*, 2004). However, where downscaling is needed

for a regional application of GCM data, there are three general methods used throughout the literature: change factors, dynamic downscaling and empirical/statistical downscaling.

2.3.1 *Change Factors*

Change factors are often used to quantify the regional effects of climate change using GCM output. Climate change is calculated for a climate variable by comparing a predicted GCM value (30-year average centred on 2020s, 2050s and 2080s) from a baseline value (i.e. 1961-1990 average). Mearns *et al.* (2001) suggested that differences are best used to indicate temperature changes, where as ratios are best suited for describing precipitation, vapour pressure and radiation changes. Once the change factor is calculated, it can then be applied (added or multiplied) to local or regional climatologies to predict the amount of change expected for a variable at a certain time-slice (2020s, 2050s and 2080s). One can also calculate change factors for variables not directly outputted by a GCM by deriving them using other GCM variables such as potential evaporation using the Penman-Monteith equation (Diaz-Nieto and Wilby, 2005). Although change factors are a popular choice for a cost-effective assessment of regional climate change, there are several limitations to using this downscaling technique. First, it is assumed that the temporal and the spatial variability of the variable in question over a time series remains constant. Second, Wilby *et al.* (2004) note that change factors assume that a change detected over a GCM grid can be translated into a change in regional climate. As previously mentioned, variables predicted for an individual GCM grid cells cannot be used to accurately portray the variability of regional climate processes occurring at sub-grid scales. To better resolve the temporal and spatial

resolution of GCM output than the change factor method, one could use dynamic or statistical downscaling techniques.

2.3.2 *Dynamic Techniques*

Dynamic downscaling technique involves nesting a higher resolution climate model within a GCM grid to resolve regional processes, such as convective or orographic precipitation, better than the GCM itself (Wilby *et al.*, 2000). These models are initialized by the atmospheric conditions supplied by a GCM bounding a specified domain. Also the nested models simulate variables at a much finer spatial scale of 20-50 km relative to a GCM, such as the Canadian RCM 3.6 illustrated in Figure 2.6 (Wilby *et al.*, 2000). When compared to the Canadian GCM 2 output grid depicted in Figure 2.5, it can be seen that the nested grid better represents regional heterogeneity, where the Great Lakes are defined and the topography of the Rocky Mountains are illustrated more prominently.

Figure 2.6 Canadian RCM3.6 45km x 45km output grid of Canada (CCCma, 2005).

Although dynamic downscaling appears to resolve the spatial issue of a GCM, there are a number of limitations. First, the accuracy of the results depends on the bias of the GCM output providing the boundary conditions that may compound and pass on uncertainty through to the nested model (Varis *et al.*, 2004). Second, these nested models are exceptionally demanding computationally making them expensive to run, limiting the researcher to the number of potential experiments and simulations that could be performed (Wilby *et al.*, 2002). Third, the dynamic technique results are still in the form of spatial averages that may not be acceptable to use in certain situations needing very finer spatial resolution, such as explicit hydrological models. In this case, further downscaling of the results may be required to individual sites that are usually done relatively simpler empirical techniques (Coulibaly and Dibike, 2004). Last, Wood *et al.* (2004) also notes the dynamic nested models may not be suitable for hydrologic simulation purposes without a bias-correction step.

2.3.3 Empirical/Statistical Techniques

The empirical/statistical downscaling technique relies on empirically based relationships or correlation between local (predictand) and global-scale (predictor) variables (Mearns *et al.*, 2003). Statistical downscaling is a popular method of downscaling GCM output data because of the low computational demand that allows for a generation of many climate scenarios (Wilby *et al.*, 2000; von Storch *et al.*, 2000). Second, a relatively small number of parameters are needed to use this technique, making it an appealing choice for hydrologic applications (Wilby *et al.*, 2000). However, one must be aware of three major assumptions made when utilizing this technique (Giorgi *et*

al., 2001; Goodess *et al.*, 2001; Mearns *et al.*, 2003; Wilby *et al.*, 2004). First, we must assume that the predictor variables produced by a GCM are realistically modelled. Second that the predictor variables represent the climate change signal. Last, we assume that the predictand/predictor relationship remains valid under future climate conditions, which unfortunately is impossible to confirm.

Furthermore, several limitations have been outlined in the literature pertaining to statistical downscaling. First, a long and reliable daily time-series of local meteorological data may not be readily available for the area of interest (Goodess *et al.*, 2001; Wilby *et al.*, 2004). Second, this technique is still affected by the biases in the underlying GCM used as the predictor variables (Goodess *et al.*, 2001). Last, Wilby *et al.* (2004) observed that potential studies in semi-arid or tropical locations may not produced results as well as for mid latitude locations. Although there have been a number of limitations to this approach, several empirical/statistical techniques have been developed and improved upon this past decade. These techniques can be generally categorized as one of three major statistical downscaling strategies: Weather generators, weather typing schemes, and transfer/regression models.

Weather generators produce climatologies at a single point using the statistical attributes of observed local climate variables. These models reproduce the representation of precipitation occurrence and transitions between wet and dry days using a Markov chain approach (Hughes *et al.*, 1999; Wilks and Wilby, 1999). One of the most well-known weather generators is the Long Ashton Research Station Weather Generation (LARS-WG) that simulates single site data under both current and future climate conditions (Semenov and Barrow, 1997; 2002). This model is particularly useful when

attempting to generate a daily-time series for a single site or region using monthly climate change scenario output.

The weather typing downscaling technique involves grouping local meteorological variables into classes of atmospheric circulation patterns (Hay *et al.*, 1991; Lapp *et al.*, 2002). Future circulation patterns are then constructed using a GCM and compared to the local or regional atmospheric circulation patterns. The comparison between GCM produced and locally observed circulation patterns are correlated either by regression or other transfer techniques to develop a climate change signal at the regional scale (Wilby *et al.*, 2002). One limitation to this downscaling technique is its inability to simulate rare or extreme events and is dependent entirely on surface-circulation relationships (Wilby *et al.* 2002). What is recognized as the most significant limitation to weather typing schemes is that changes in precipitation observed through changes in frequencies of weather patterns are rarely consistent with precipitation changes produced by the host GCM, unless additional predictors such as atmospheric humidity are used (Wilby *et al.*, 2002).

Regression models operate by drawing linear or non-linear relationships between global scale predictor variables and local-scale predictand variables (Wilby *et al.*, 1998). Common regression methods used are multiple regression, such as the Statistical Downscaling Model (SDSM) (Wilby *et al.*, 2002), canonical correlation analysis (CCA) (von Storch *et al.*, 1993), and artificial neural networks (Crane and Hewitson, 1998). A major advantage of using regression based downscaling is the low computational power and relative ease of application (Wilby *et al.* 2002). However, regression based approaches are known to underestimate precipitation because of the low predictability of

local precipitation based on global scale forcings (Bürger, 1996; von Storch, 1999).

Furthermore, Wilby *et al.* (2002) stated that this technique poorly predicts extreme events because these anomalous occurrences lie at the margins or beyond the range of the data set used to calibrate the model.

2.4 Knowledge Gaps and Research Opportunities

As discussed in Chapter 1, there has been no assessment throughout the literature pertaining to dataset selection used to calibrate the SDSM for use not only in southwestern Ontario but worldwide. There is need to determine if the NCEP/NCAR reanalysis suggested to be used by the developers (Wilby *et al.*, 2002) of the SDSM is most appropriate choice for calibration when downscaling for certain local-scale variables being used for various applications, such as climatic and hydrologic prediction. This is not only an important research question because the SDSM is the first downscaling tool offered to the broader, less specialized climate change community (e.g. conservation authorities or private consulting companies), but also because this model is currently being recommended by the Canadian Climate Impacts and Scenarios (CCIS, 2007).

Furthermore in a broader context, although there is a substantial amount of literature pertaining to case studies using GCMs and downscaling techniques to predict climate change, there is a need for more downscaling research in southwestern Ontario. Much climate research done in this area has used GCM data without downscaling, to predict climatic variables for a regional use. Of this research, there still lacks a clear consensus pertaining to the direction or trajectory of the regions climate. Mortsch *et al.*

(2000), Bellamy *et al.* (2002), Lofgren *et al.* (2002), and Booty *et al.* (2005) have all illustrated this lack of a agreement by attempting to assess the extent of precipitation and temperature change using two outdated GCMs, the CGCM1 (Canadian Centre for Climate Modelling and Analysis (CCCma)) and HadCM2 (Hadley Centre for Climate Prediction and Research). These studies found conflicting results where the CGCM1 predicted a large temperature change and a decrease in precipitation where the HadCM2 predicted a smaller temperature change and an increase in precipitation. However, Kutzbach *et al.* (2005) found when using eight different GCMs and two different scenarios that there would be an increase of precipitation in the Great Lakes region in the future. In addition to resolving this disagreement in GCM results for southwestern Ontario, another aspect of literature currently under-researched in this discipline is the application of different downscaling techniques southern Ontario (Wilby *et al.*, 2002; Cunderlik and Simonovic, 2005). In this region planners will need to draw from the literature to create reliable climate forecasts in the near future when attempting to reassess present day water use and allocation policies, structures, and navigation systems among other concerns within the water sector of southwestern Ontario.

CHAPTER 3: METHODS

The SDSM is a hybrid of a stochastic weather generator and regression-based model where large-scale atmospheric variables are correlated to local-scale variables (Wilby *et al.* 1999; 2002). The generation of future local-scale climate scenarios from GCM data relies on the pivotal identification of past relationships between local occurrences and the global-scale atmospheric state using reanalysis data. Throughout the SDSM literature the NCEP/NCAR reanalysis has been the only dataset used to represent the past global-scale atmospheric state since there is insufficient data measured to assess the global state of the atmosphere at any one time (Wilby *et al.*, 2002; Dibikey and Coulibaly, 2004; Diaz-Nieto and Wilby, 2005; Gagnon *et al.*, 2005; Khan *et al.*, 2006). However, there is need to determine if the NCEP/NCAR reanalysis is the best choice for use in the SDSM where there may be a more appropriate choice of reanalysis for SDSM calibration when downscaling for certain local-scale variables for various applications, such as climatic and hydrologic prediction. Thus this thesis aims to evaluate the ability of the SDSM to downscale daily precipitation and temperature time-series from GCM output data for use in southwestern Ontario when calibrated by either the NCEP/NCAR or ECMWF reanalysis. The strength of both the NCEP/NCAR and ECMWF calibrated models will be assessed through direct comparison between the model errors of the downscaled daily PREC, TMAX and TMIN to the observed time-series.

3.1 Study Area

To illustrate the sensitivity of the SDSM to reanalysis products when downscaling for precipitation and temperature scenarios, southern Ontario was selected for this study due to the spatial and temporal variation of the seasonal temperature and precipitation, as well as a current need for future regional climate predictions. The climate of southern Ontario has been characterized as temperate, with considerable local and temporal variation. These spatial and temporal differences can be attributed to local topography, proximity to the Great Lakes, as well as the prevailing westerly winds of the area (Sanderson, 2004). The mean summer temperatures are approximately 19°C, whereas the mean winter temperatures are approximately -7°C (Sanderson, 2004). Mean annual precipitation in southwestern Ontario, ranges from approximately 800mm to 1000mm (Singer *et al.*, 2003). The topography of southern Ontario is characterized by glacial formations, having relief from 45m above sea level in the Ottawa River Valley to 550m above sea level in the Collingwood Region (Singer *et al.*, 2003). More specifically for this study, the southwestern region of Ontario covered by the predictor grid cell used to generate downscaled scenarios from the GCM output data for the Brantford MOE station is defined as the area from the latitude 43.75°N to 41.25°N and longitude 81.25°W to 78.75°W, covering approximately 60,000 km² (Figure 3.1).

Figure 3.1 Predictor cell used to downscale for the Brantford MOE meteorological station in southwestern Ontario.

To further assess these SDSM calibrated models, the Grand River basin was also selected as the site for a hydrologic application for this study (Figure 3.2). The Brantford meteorological station for which the downscaled precipitation and temperature scenarios were generated from the various GCM output data, is located in the south central region of the basin. The Grand River basin is one of the largest in southwestern Ontario (~7,000 km²), draining the Grand River (~300km) from Dundalk, Ontario to outside of Dunnville, Ontario into Lake Erie, as well as the Speed, Eramosa and Nith tributary rivers among many other smaller creeks and streams (GRCA, 2007). The larger urban areas within the basin include the cities of Guelph, Cambridge, Kitchener/Waterloo and Brantford, as well as many rural towns (pop. 925,000 (SWP, 2007)). Although these urban areas are expanding, the predominant landuse within the basin is mainly agricultural.

Figure 3.2 The Grand River basin located in southwestern Ontario.

The expansion of intensive agricultural practices and rapid growth on urban fringes in the Grand River area are thus increasing the demand for fresh water from either the groundwater reservoirs or surface reservoirs, such as lakes and rivers (de Loë *et al.*, 2001; Carter *et al.*, 2005). Currently, 28% of the water used for the municipalities in this area is extracted directly from the Grand River and these uses are assumed to increase in the future (SWP, 2007). The projected changes of water use and availability are creating the need for new management techniques to achieve maximize efficiency of reservoir storage in the future for the Grand River Basin.

The Grand River Conservation Authority (GRCA), the responsible authority for the social and financial with the basin, will require accurate climatological data to predict the temporal and spatial hydrologic variability within watersheds. Thus, the general study area selected was the Grand River basin to determine the validity of the two calibrated SDSM models to generate climatic scenarios to be implemented for

hydrological modelling. More specifically, the Fairchild Creek watershed ($\sim 400 \text{ km}^2$) within the Grand River basin was selected as the study area for the hydrologic application of the downscaled scenarios due to the availability of a previously developed database and a validated and calibrated hydrologic model for this location (Sheng, 2005; Bonnycastle, 2006) (Figure 3.3).

Figure 3.3 The Fairchild Creek watershed located in southwestern Ontario.

3.2 SDSM Data Requirements

The following section outlines the local- and global-scale data necessary to run the SDSM. The SDSM correlates the local- and global-scale atmospheric variables to produce the parameters for calibrating the regression-based downscaling model. The SDSM data requirements for each step of the downscaling process will be described in the subsequent section (3.3).

1. Local-Scale Station Data (*predictands*):

Time-series of daily precipitation (PREC), and maximum and minimum temperatures (TMAX and TMIN respectively) for the period 1961-1990 time-series were obtained from the Brantford MOE (6140954) meteorological station (43°8'N, 80°14'W, 196m) (EC, 2003). The 1961-1990 time-series was chosen based on the availability of the historical data (i.e. number of missing values and measurement error respectively).

2. Global-Scale Data (*predictors*):

Two datasets including a suite of daily atmospheric variables used to represent the past global-scale atmospheric variables for the SDSM were supplied by the NCEP/NCAR 50-year reanalysis (NRA50) (Kistler, *et al.*, 2001) and the ECMWF 40-year reanalysis (ERA40) (Uppala *et al.*, 2005) for the period 1961-1990 (Table 3.1). As for the daily atmospheric variables needed to generate scenarios representing the “future” global-scale atmospheric variables, four GCM output datasets were supplied by various climate centers maintained by the IPCC 4th Assessment Model Output database (IPCC, 2006) (Table 3.1). The 1961-90 climatology was obtained from the 20th Century scenario

Figure 3.1 Predictor datasets obtained for generating downscaled scenarios.

Datasets	Name	Model	Climate Centre	Resolution
Reanalysis	NRA50	NRA	National Centres for Environmental Prediction/ National Centres for Atmospheric Research	2.5° x 2.5°
	ERA40	ERA	European Centre for Medium-Range Weather Forecasts	2.5° x 2.5°
GCM	BCCR	BCM2	Bjerknes Centre for Climate Research	2.76° x 2.81°
	CCCMA	CGCM3.1	Canadian Centre for Climate Modelling and Analysis	2.76° x 2.81°
	CNRM	CM3	Centre National de Recherches Meteorologiques	2.76° x 2.81°
	MPI	ECHAM5	Max Planck Institute for Meteorology	1.85° x 1.875°

produced by the four GCMs where the GHG concentrations followed observation and matched the IPCC Special Report on Emission Scenarios (SRES) concentrations at the year 1990 (IPCC, 2004). Table 3.2 illustrates the set of daily predictors that were extracted from the two reanalysis and four GCM datasets to be used to derive the downscaled scenarios. In addition, the one-day lagged values for each of the predictor variables were created to account for any auto-correlation between the predictand and the predictor variables.

Table 3.2 Predictor variables obtained for downscaling procedure.

Predictor Variables	Atmospheric Level		
	Surface	850hPa	500hPa
2 Meter Surface Temperature	temp	--	--
Mean Sea Level Pressure	mslp	--	--
Specific Humidity	shum	s850	s500
Relatively Humidity	rhum	r850	s500
Zonal Velocity (E-W)	p__u	p8_u	p5_u
Meridonal Velocity (N-S)	p__v	p8_v	p5_v
Vorticity ^a	p__z	p8_z	p5_z

^a Secondary variable derived following the methods of Jones *et al.* (1993)

To ensure that the spatial resolutions of all four GCMs and the reanalyses were identical, the GCMs were re-gridded to conform to the 2.5°x2.5° grid of the NRA50 and ERA40 dataset. An inverse distance weighted interpolation technique was utilized to re-grid each cell of the global field based on the weighted average of surrounding grid cells where the weight of a cell decreased with increasing distance. As a final step, the required atmospheric variables extracted from the GCMs and reanalyses (predictors) were normalized to their respective 1961-1990 climatology. Normalization converts the daily data into standardized anomalies from the monthly mean, ensuring that the

downscaled scenarios are not compromised by the systematic biases contained within the reanalysis and GCM predictors.

3.3 SDSM Procedure

To assess the sensitivity of the SDSM to the reanalysis products (NRA50 and ERA40), the SDSM was first used to downscale daily precipitation (PREC), and maximum and minimum temperatures (TMAX and TMIN) using both the NRA50 and ERA40. The detailed steps to generate the downscaled scenarios using the SDSM version 3.3 from the GCM data for this study are outlined in Wilby *et al.* (2002) and Wilby and Dawson (2004). Figure 3.4 schematically illustrates the SDSM procedure and data needs which are outlined below in the following sub-sections.

Figure 3.4 Schematic diagram of the SDSM process (a) and data requirements (b).

3.3.1. Screening Variables

All statistical downscaling techniques rely heavily upon the relationships between a suite of global-scale predictors that are used to empirically correlate to the local-scale predictands. However, the user must select only those global-scale predictors appropriate for relating to the predictand. Thus, the user must screen the available predictor variables using monthly percentages of explained variance to quantitatively determine the most appropriate predictors to be selected for building the regression model. The monthly percentage of explained variance allows the user to determine the ability of a certain predictor to explain climatic variability occurring at the regional scale (predictand) for each month. Therefore, the same atmospheric variables supplied by the reanalysis for calibrating SDSM must also be supplied by the GCM to generate future scenarios. For this study, three predictands (PREC, TMAX and TMIN) were screened with respect to two reanalyses supplying the suite of predictors (NRA50 and ERA40) to calibrate the regression model.

3.3.2 Calibration

To calibrate the SDSM, regression models for every month of the year are constructed with the relationship between predictand and selected predictors. The calibration of the SDSM only utilizes the first 15 years of the station (predictand) and reanalysis (predictors) datasets to reserve the last 15 years to validate the calibration. A stochastic component of the SDSM artificially inflates the variance of the generated scenario daily time-series to compensate for the regression that does not explain all observed variance of the predictand. Furthermore, the SDSM is capable of modelling

both conditional processes, such as precipitation, and unconditional processes using the regression relationships (Wilby and Dawson, 2004). For this study, the three predictands, PREC (conditional), TMAX and TMIN (unconditional) were linearly correlated to the selected predictors of the two reanalyses (NRA50 and ERA40) to calibrate the multiple linear regression model. However, for others studies where the predictand data may be severely skewed, the data may need to be transformed to retain the assumption of the predictand and predictor relationships are linear. The regression techniques used to build and calibrate the regression models for PREC (magnitude and occurrence), TMAX and TMIN are explained in detail within Wilby *et al.* (1999; 2002) and are summarized below.

3.3.2.1 Daily Precipitation Occurrence and Amount

To calibrate the model for PREC, a “conditional” process, two regression models were built. The first being for the occurrence of daily precipitation (PREC) (3.1) which determines the daily probability of non-zero precipitation (wet-day) O_i for a given day i :

$$O_i = \alpha_0 + \alpha_A A + \alpha_B B + \dots \quad 3.1$$

where the α are the parameters estimated from the correlation between the predictand (PREC) and $A, B \dots$ predictors, supplied by either NRA50 or ERA40, determined from the screening process. To determine whether precipitation occurred on a given day, a linear random number r_i ($0 \leq r_i \leq 1$) is generated, where precipitation occurred if the

random number generated was less or equal to the probability of non-zero precipitation²
($r_i \leq O_i$).

A second regression model (3.2) is needed to downscale the amount/magnitude when PREC has occurred (i.e. if $r_i \leq O_i$). Thus, the regression model for precipitation amounts (P_i) for a given wet-day i :

$$P_i = \beta_0 + \beta_A A + \beta_B B + \dots + E_i$$

where the β are parameters estimated from the correlation between the *predictand* (PREC) and $A, B \dots$ predictors, supplied by either NRA50 or ERA40, and E_i is random or modelling error. To account for this error, the expected daily precipitation amount is modelled (3.3) using an empirically derived correction ratio (c_R) to equal the observed mean amount of the calibration period:

$$E(P_i) = \phi c_R (\beta_0 + \beta_A A + \beta_B B + \dots) \quad 3.3$$

where ϕ is a random generated scaling factor, with a mean of 1, is used to increase the variance of modelled predictand (PREC) to better agree with the observed predictand.

3.3.2.2 Daily Maximum and Minimum Temperature

To calibrate the regression model for both TMAX and TMIN, temperature (T_i) (3.4) for a given day i were modelled using:

$$T_i = \delta_0 + \delta_A A + \delta_B B + \dots + E_i \quad 3.4$$

where the δ are the parameters estimated from the correlation between the predictand (PREC) and $A, B \dots$ predictors, supplied by either NRA50 or ERA40, and E_i is random or modelling error. Unlike the model to determine the precipitation amount (3.2 and 3.3), E_i is modelled randomly using a Monte Carlo simulation, where the error was assumed to be normally distributed with a standard deviation equal to the standard error of the regression equation.

3.3.3. Validation

Once the SDSM has been calibrated, the NRA50 and ERA40 model calibrations must be verified through synthesizing daily time-series of the using the last 15 years (1975-90) of the predictand and predictor variables. Although the stochastic component of the SDSM allows for the synthesis of up to 100 different ensembles of time-series, only 20 ensembles were simulated for this study. For the purposes of this study, we selected the PREC, TMAX and TMIN ensemble that most closely correlated with the observed time-series for each of the calibrated model (NRA50 and ERA40) for comparative consistency throughout the statistical analyses. However, each synthesized ensemble can be considered a plausible scenario for validating model calibration.

To assess the calibration of the NRA50 and ERA40 models for downscaling PREC, TMAX and TMIN, Root Mean Square Error (RMSE) (3.5) and the Pearson's Coefficient of Determination (R^2) (3.6) were calculated. The RMSE analysis determined the model errors between the observed and synthesized 1975-1990 time-series, and the R^2

calculation was used to determine the proportion of variability within the observed data accounted for by the NRA50 and ERA50 models. The RMSE is given by:

$$\text{RMSE} = \left(\frac{1}{n} \sum_{i=1}^n (P_{fi} - P_{oi})^2 \right)^{0.5} \quad 3.5$$

where P_{fi} is the monthly forecasted predictand (i.e. PREC, TMAX or TMIN), P_{oi} is the monthly observed predictand, and n is the number of monthly values (Lettenmaier and Wood, 1993). As for R^2 , it is given by:

$$R^2 = \left[\frac{\sum_{i=1}^n (P_{fi} - \bar{P}_f) (P_{oi} - \bar{P}_o)}{\sum_{i=1}^n (P_{fi} - \bar{P}_f)^2 \sum_{i=1}^n (P_{oi} - \bar{P}_o)^2} \right]^2 \quad 3.6$$

where $\bar{P}_f$ is the mean monthly forecasted predictand (i.e. PREC, TMAX or TMIN), $\bar{P}_o$ is the mean monthly observed predictand for the synthesis period, and n is the number of monthly values. An R^2 value of 1.0 indicated that 100% of the observed variance was accounted for by the forecasted variance (Lettenmaier and Wood, 1993).

3.3.4. Scenario Generation

The last step of the SDSM process is to generate the “future” local-scale predictand using the regression models where the global-scale GCM data are inputted into the models representative of the “future” predictors. In this study, the daily predictands (PREC, TMAX and TMIN) were downscaled using the four 1961-90 GCM datasets; once the NRA50 and ERA40 models had been calibrated and validated, a similar process to the model validation is undertaken. A suite of ensembles for each

predictand data series for the whole of the 1961-90 period was generated using predictor variables supplied by the four GCMs. Again, the downscaled scenario ensemble correlating best to the observed time-series was to select for statistical analysis. It should be noted that when generating future scenarios, using this approach to select an ensemble for statistical analysis is not possible as there is no observed equivalent. However, each generated ensemble can be considered a plausible downscaled scenario.

3.4 Statistical Analysis of Downscaled Results

To compare the performance of the NRA50 and ERA40 calibrated models, this study will focus on evaluating the estimates of monthly means and variances in comparison to those of the observed time-series. Exploratory data analysis and error in estimates in means and variances (Coulibaly and Dibike, 2004; Gagnon *et al.*, 2005; Khan *et al.*, 2006) was used to assess model performances of reproducing the observed time-series of the downscaled *predictands* (PREC, TMAX and TMIN) to identify the most appropriate and reliable downscaling model (NRA50 vs. ERA40).

3.4.1 Exploratory Data Analysis

Exploratory data analysis of the observed time-series was needed to determine the most appropriate statistical test (parametric versus non-parametric) to be performed based on the normality, outliers and autocorrelation of the time-series. Based on the results of the analyses presented in section 4.2.1, non-parametric approaches were selected to evaluate the downscaled results obtained using the two reanalyses. To perform a parametric analysis the data must be normally distributed and independent (i.e. not

serially correlated). To determine whether the data are nearly normal and contain outliers, histograms and density plots were constructed. Autocorrelation function (ACF) plots were also used to determine any serial correlation within the data series.

3.4.2 Model Error Evaluation in Estimates of Means and Variance

The differences between the means of the downscaled data (NRA50 and ERA40) with respect to the observed data were assessed using a hypothesis testing for differences between means. The non-parametric Wilcoxon Rank-Sum test (Wilcoxon, 1945), also referred to as the Mann-Whitney U test, determines a p value for estimating the difference between two population means ($\mu_1 - \mu_2$). For this study, if $p < \alpha$ the null hypothesis would be rejected where one would conclude a difference between the two samples with 95% confidence ($\alpha = 0.05$). If $p > \alpha$ the null hypothesis was accepted, concluding that there was no difference of means between the two samples ($\alpha = 0.05$). The null hypothesis (H_0) tested in this study was that there was no significant difference between the monthly means of the downscaled (NRA50 or ERA40) and the observed data for PREC, TMAX and TMIN.

To evaluate the equality of two population variances, the Levene test (Levene, 1960), as modified by Brown and Forsythe (1974) was adopted for this study. The original version proposed by Levene (1960) considered only the distances of the data from the sample mean, whereas Brown and Forsythe (1974) included the median as well as the mean showing to be more robust for a skewed data-series than the original. Similar to the difference between means, the null hypothesis (H_0) for the Levene test was that there was no significant difference of equality between variances of the downscaled

(NRA50 or ERA40) and the observed data for the monthly PREC, TMAX and TMIN data.

Furthermore, to quantify the uncertainty of the observed and downscaled daily PREC, TMAX and TMIN, 95% confidence intervals can be plotted around the estimates of means and variances for each month. For the purposes of this study, the 95% confidence intervals for the estimates of the means and variances were completed using a non-parametric bias-corrected and adjusted (BCa) bootstrapping approach (with replacement) (Efron and Tibshirani, 1993; Czado and Munk, 2001). The means and variances of 1000 samples were drawn from the original datasets and the 2.5th and 97.5th percentiles were determined.

3.5 Hydrologic Application

The SDSM is openly available to the public as an approach to downscale a collection of predictands to be used as future regional-scale climatic variables for various applications such as hydrologic modelling. In addition to the evaluation of the downscaled scenarios as described above, it is necessary to examine the impact of the differences in these scenarios on output from a hydrologic model. Studies undertaken to determine if climatic variables produced by the SDSM could be used to simulate streamflow included Wilby and Dettinger (2000) in California, Gagnon et al. (2005) and Coulibaly and Dibike (2005) in Québec, and Diaz-Nieto and Wilby (2005) in the United Kingdom. These studies concluded that the SDSM does produce reasonable downscaled scenarios for hydrologic prediction using various GCMs and hydrologic models. However, there is a need to assess the hydrologic application of SDSM products for

basins within southwestern Ontario. Thus, the downscaled PREC, TMAX and TMIN scenarios produced for this study were used as the climatological inputs into the Soil and Water Assessment Tool version 2003 (SWAT) hydrologic model to simulate daily river streamflow, using the ArcView 3.3 extension AVSWAT-X version beta 2.01. These daily streamflow simulations were used to further assess the ability of the two calibrated models (NRA50 and ERA40) to produce appropriate climatic inputs needed by the hydrologic model.

3.5.1 Soil and Water Assessment Tool (SWAT)

Predominantly used to simulate water quality variables and erosion-prone areas within watersheds, the SWAT is a semi-distributed hydrologic model. SWAT users attempt to generate water quality, soil and nutrient erosion on a daily time step based on changes to certain agricultural management scenarios in relatively large, ungauged watersheds. The SWAT model calculates surface runoff using the United States Soil Conservation Service (SCS) Curve Number method, empirically relating potential runoff to landuse and soil type, and daily potential evapotranspiration using the Priestly-Taylor method based. Additionally, SWAT is capable of simulating sediment and nutrient yields, among other variables not studied for this research. The detailed steps to simulate runoff as well as these other variables are outlined in (Arnold *et al.*, 1998; Neitsch *et al.*, 2002a).

SWAT has successfully been implemented throughout North America to simulating river runoff as well as sediment erosion and yield (Arnold *et al.*, 1993; van Liew and Garbrecht, 2003; Saleh and Du, 2004; Jayakrishnan *et al.*, 2005). The SWAT

model has been calibrated and validated for many watersheds with differing spatial scales, from less than 10 to thousands of km² (Srinivisan *et al.*, 1998; Spruill *et al.*, 2000; Borah and Bera, 2004; Bosch *et al.*, 2004; Govender and Everson; 2005).

For the purposes of this study, the SWAT model was selected to simulate river runoff for the Fairchild Creek watershed due to the relatively low computational demand needed in comparison to a fully distributed model. Furthermore, the Fairchild Creek watershed was selected due to its proximity to the Branford MOE meteorological station for which downscaled scenarios were generated for this research. Using the entire Grand River basin would have been beyond the scope of this research due to the number of meteorological stations needed to represent the climatic heterogeneity of the area. Finally, the SWAT calibration parameters for the Fairchild Creek watershed have been previously determined and were obtained from the research undertaken by Bonnycastle (2006), who investigated the environmental and economic implications of land management changes in this watershed.

3.5.2 SWAT Data Requirements

The following section outlines the spatial data (Table 3.3) required to set up the SWAT base model and the climatological data (Table 3.4) needed to simulate daily streamflow once the base model has been constructed. Additionally, the observed streamflow data used to assess the predictive ability of the SWAT model to simulate river runoff will be outlined as well. The subsequent section (3.5.3) will describe the data requirements for the SWAT base model setup and daily streamflow simulations.

Table 3.3 Spatial input data required for SWAT simulation for the Fairchild Creek watershed (adapted from Bonnycastle, 2006).

Input	Use	Spatial Scale	Last Updated	Source
Digital Elevation Model (DEM)	Derived hydrological parameters (watershed, sub-basins, slope and stream network)	1:10,000 30m resolution	2000	GRCA (2000a)
Landuse/Landcover	Derive Hydrologic Response Units (HRUs) and, drives rainfall/runoff and sediment transport processes	1:1,000,000 30m resolution	2000	GRCA (2000b)
Soil Data	Derive Hydrologic Response Units (HRUs) and, drives rainfall/runoff and sediment transport processes	Brant County (1:15,840) Waterloo County (1:20,000) Wellington County (1:63,360) Wentworth County (1:63,360)	1989 1971 1963 1965	Acton (1989a,b) Presant and Wicklund (1971) Hoffman <i>et al.</i> (1963) Presant <i>et al.</i> (1965)
Additional Sub-basin Outlets	Specifies location of point outlets	1:10,000	1997	GRCA (1996)

Table 3.4 Climatic input data required for SWAT simulation for the Fairchild Creek watershed (adapted from Bonnycastle, 2006).

Input	Use	Temporal Scale	Period	Source
Observed PREC, TMAX, TMIN	Drives rainfall/runoff processes	Daily	1961-1990	Environment Canada (2003)
Downscaled PREC, TMAX, TMIN 1. NRA50 2. ERA40	Drives rainfall/runoff processes	Daily	1961-1990	SDSM Scenario Generation (see section 3.3.4)
Solar Radiation, Wind Speed and Relative Humidity	Drives evapotranspiration processes	Daily	1961-1990	Environment Canada (2006)

1. Spatial Input Data:

To set up the base model of SWAT, spatial inputs are required to delineate the hydrologic boundaries, inputs and parameters of the Fairchild Creek watershed. The main spatial data requirements for the SWAT model for the Fairchild Creek watershed include a digital elevation model (DEM), landuse/landcover data, soil, as well as sub-basin outlet data for this study. Table 3.3 lists the type, use and sources of each of the spatial datasets. Last, attribute tables were created to define the spatial location of the meteorological stations and flow gauges used to for this research. The pre-processing needed to format all the spatial data inputs for the SWAT model for the Fairchild Creek watershed is described in Sheng (2005) and Bonnycastle (2006).

2. Climatological Input Data:

Table 3.4 outlines the type, use and sources of each of the climatic inputs used in the SWAT model for this study. To simulate daily streamflow using the SWAT model, the required climatological inputs were daily PREC, TMAX and TMIN. The daily observed and downscaled PREC, TMAX and TMIN datasets were used to simulate daily streamflow for the period of 1961-1990. First, the observed daily PREC, TMAX and TMIN were obtained from the Brantford MOE meteorological station, previously described for the SDSM procedure in section 3.2, were used to simulate daily streamflow. However unlike the SDSM, the SWAT model required continuous PREC, TMAX and TMIN time-series including no missing values. For those days missing data, the value recorded at the Hamilton A (6153194) meteorological station (43°10'N, 79°56'W, 238m) (EC, 2003) was substituted. The Hamilton A station was selected as the surrogate for

missing data due to its proximity to the Brantford MOE station and the availability of the 1961-90 dataset. Second, the downscaled daily PREC, TMAX and TMIN scenarios generated from the four GCMs using the NRA50 and ERA40 calibrated models for the Brantford MOE station described in section 3.3.4 were each used respectively to simulate daily streamflow.

Additionally, daily solar radiation, wind speed and relative humidity 1961-1990 time-series were required to drive the evapotranspiration processes of the model. These variables were derived from the 1961-1990 monthly climate normals obtained from the Waterloo-Wellington A (6149387) meteorological station (43°27'N, 80°23'W, 317m) (EC, 2006) using the SWAT weather generator. When generating daily solar radiation and relative humidity, the influence of precipitation in the generated scenarios is accounted for by adjusting for overcast conditions. As for wind speed, the daily dataset is generated randomly based on the 1961-1990 climatology introducing temporal inconsistency when attempting to compare the daily streamflow simulated from the various NRA50 and ERA40 scenarios. However, this problem was avoided as the Priestly-Taylor equation was selected as the method of calculating daily evapotranspiration which does not require wind speed unlike the Penman-Monteith equation (Neitsch *et al.*, 2002b).

Figure 3.5 illustrates the spatial locations of the meteorological stations supplying the climatic data inputs used to simulate streamflow for the Fairchild Creek watershed for this research.

Figure 3.5 The location of the flow gauge and meteorological stations within the Fairchild Creek watershed.

3. Streamflow Gauge Data:

The “Fairchild Creek near Brantford” flow gauge ($43^{\circ}8'51''\text{N}$, $80^{\circ}9'17''\text{W}$) (EC, 2001) supplied the observed daily flow rates for this watershed for the period 1965-1990 (Figure 3.5). The 1965-1990 time-series was obtained rather than the 1961-1990 time-series obtained for the climatic data inputs due to data availability.

3.5.3 *SWAT Procedure*

The detailed steps to simulate streamflow using the SWAT version 2003 model for the Fairchild Creek watershed used for this study are outlined in Bonnycastle (2006) and summarized below.

3.5.3.1 Base Model Setup

First, the base model of SWAT was set up using the spatial data inputs to delineate the hydrologic boundaries, inputs and parameters, acting as the physical representation of the Fairchild Creek watershed. The digital elevation model (DEM) input layer was used to delineate the Fairchild Creek watershed boundary and sub-catchments as well as slope and stream networks. To determine the rainfall-runoff characteristics of each of the DEM defined sub-catchments for the base model, hydrologic response units (HRUs) were produced using the landuse/landcover and soil data. The landuse/landcover data provided by the GRCA and soil data provided by the Ontario Soil Survey were converted into the SWAT database format by Sheng (2005). Each the rainfall-runoff characteristics defined by the HRUs drive the flow and sediment functions of the SWAT model for each sub-catchment. For this research, rather than selecting one single HRU for each sub-catchment, a weighted average of HRUs based on size was calculated to account for heterogeneity of each sub-catchment in terms of the rainfall-runoff characteristics. For an HRU to be delineated within a sub-catchment, landuse/landcover and soil type had to cover at least 10% of the area. Last, point outlets could be delineated in the base model to represent any additional flow entering the stream network. However, the point outlet data provided by the GRCA did not define any point outlets within the Fairchild Creek watershed.

3.5.3.2 SWAT Calibration/Validation

The calibration and validation of the SWAT model was previously undertaken by Bonnycastle (2006) for the Fairchild Creek watershed using the identical base model

described in the previous section. The SWAT model was calibrated and validated using observed and simulated daily streamflow data at the “Fairchild Creek near Brantford” flow gauge. Three years of daily data (1998-2000) was used to calibrate and the three subsequent years of daily data (2001-2003) was used to validate the SWAT model. The monthly total observed and simulated discharges produced during the model validation were compared using the Nash-Sutcliffe coefficient and percent deviation of runoff volume to determine the most appropriate calibration parameters. A sensitivity tool provided by the SWAT AVSWAT-X extension was used to determine those parameters most sensitive when adjusted iteratively. Subsequently, Bonnycastle (2006) manually adjusted parameters based on the sensitivity analysis until the Nash-Sutcliffe coefficient was maximized and percent deviation of runoff volume was minimized, with the condition that the parameters maintained hydrologic correctness. Using the “best-fit” calibration parameters, the Nash-Sutcliffe coefficient obtained indicated a moderate predictive efficiency (0.4925) and the percent deviation of runoff volumes indicated slight over-estimation of water yield (5.5%). These less than optimal validation results obtained by Bonnycastle (2006) were attributed to the distribution of wetland areas throughout the Fairchild Creek watershed that were not accounted for within the SWAT model. Thus, the streamflows simulated from the downscaled output (NRA50 and ERA40) were statistically compared to those simulated by the observed climatic data, and not to observed streamflow itself to avert this problem.

3.5.3.3 Runoff Simulations

The final step to the SWAT process was to simulate daily streamflow using the calibrated and validated model provided by Bonnycastle (2006) by inputting climatic data (PREC, TMAX and TMIN). Two sets of runoff simulations were undertaken for this study using two different sets of climatic inputs. First, observed PREC, TMAX and TMIN data obtained from the Brantford MOE station were used to simulate daily discharge for the period 1961-90. This simulation was used to compare to the observed daily discharge measured at the “Fairchild Creek near Brantford” flow gauge to determine the predictive ability of the calibrated SWAT model provided by Bonnycastle (2006). Second, the separate downscaled PREC, TMAX and TMIN scenarios generated from the four GCMs for the Brantford meteorological station respectively using the NRA50 and ERA40 calibrated models, generating eight 1961-90 daily simulation results in total.

3.5.4 Statistical Analysis of Simulated Runoff

The predictive ability of the calibrated SWAT model was first assessed using the observed climatic data (PREC, TMAX and TMIN) to determine the overall errors produced by the hydrologic model. To assess the predictive ability of the SWAT model using the observed climatic data, again RMSE and R^2 were used however comparing forecasted and observed discharge (Q_f and Q_o rather than P_f and P_o) in equation (3.5) and (3.6) previously described in section 3.3.3. Furthermore, Relative Bias (RB) (3.7) and Relative Mean Absolute Error (RMAE) (3.8) were calculated to statistically identify significant differences between simulated and observed daily streamflow. The RB was

used to analyze the overall systematic error of the simulated streamflow produced by the SWAT model. Last the RMAE analysis was also chosen to determine the validity of the two models as an indicator of the error magnitude due to the sensitivity of the RMSE calculations to a small number of large errors (Lettenmaier and Wood, 1993). The RB and RMAE are given by:

$$RB = \frac{\bar{Q}_f - \bar{Q}_o}{\bar{Q}_o} \quad 3.7$$

$$RMAE = \frac{\frac{1}{n} \sum_{i=1}^n |Q_{fi} - Q_{oi}|}{\bar{Q}_o} \quad 3.8$$

where Q_f is monthly forecasted discharge and Q_o is the monthly observed discharge, $\bar{Q}_f$ is mean monthly forecasted discharge and $\bar{Q}_o$ is the mean monthly observed discharge through the simulation period, and n is the number of monthly values. (Lettenmaier and Wood, 1993). Only the years from 1965 to 1990 were analyzed since the observed streamflow data time-series obtained from the “Fairchild Creek near Brantford” was only available for that time-period. Furthermore, the SWAT model requires start-up or “spin-up” time to begin producing a significant daily streamflow time-step, thus the observed PREC, TMAX and TMIN 1961-1990 time-series was used to simulate streamflow.

As for the second set of SWAT runoff simulations produced using the PREC, TMAX and TMIN downscaled from the NRA50 and ERA40 calibrated models, differences between estimates of means and variances of daily discharge were assessed using hypothesis testing. Again the non-parametric Wilcoxon Rank-Sum test and the Levene test described previously in Section 3.4 will be used to test assess the errors in

estimates of means and variances for each month. The null hypothesis (H_0) for these analyses was that there was no significant difference between the monthly means or variances of the simulated daily discharge produced by the observed and downscaled climatic inputs for the Fairchild Creek watershed. Since this study is assessing the downscaling the ability of the NRA50 and ERA40 to produced analogues to the observed climatic variables (PREC, TMAX and TMIN), the streamflows simulated by the four GCMs were statistically compared to those simulated by the observed climatic data, and not to observed streamflow itself. Furthermore, biases produced by the calibrated SWAT model provided by Bonnycastle (2006) will be consistently represented throughout the streamflow if the simulations produced by observed climatic inputs will serve as the comparative analogue for the NRA50 and ERA40 simulations, rather than the observed streamflow. Last, the uncertainty related to the SWAT simulations were again quantified using 95% confidence intervals around the estimates of means and variances for each month. Again, the statistical analyses were only calculated for the years 1965 to 1990 due to “spin-up” time needed by the SWAT model when producing daily time-steps although the runoff simulations were run for the 1961-1990 time period.

CHAPTER 4: RESULTS AND DISCUSSION

To determine the most appropriate reanalysis for calibrating the SDSM for downscaling daily PREC, TMAX and TMIN in southwestern Ontario, the NCEP/NCAR and ECMWF calibrated models were assessed through direct comparison to the observed time-series. The organization of this section follows the procedural steps of the SDSM required to downscale the predictands from the various GCM output datasets depicted previously in Figure 3.4. First, the results of the calibration of the NRA50 and ERA40 derived models will initially indicate the ability of the respective models for downscaling PREC, TMAX and TMIN. Second, the downscaling ability of the NRA50 and ERA40 calibrated models will be investigated in terms of validation error. Third, the analysis of the downscaled scenarios in terms of estimates of means and variances will indicate the calibrated model most appropriate for downscaling PREC, TMAX and TMIN produced from the four various GCMs. Last, the analysis of the SWAT simulations produced from the downscaled inputs will indicate the reanalysis best suited for calibrating the SDSM for the production of climatic inputs for hydrologic modelling.

4.1 SDSM Calibration and Validation

The three predictands downscaled for this study (PREC, TMAX, TMIN) were first screened with respect to the two reanalyses supplying the suite of predictors (NRA50 and ERA40), described in section 3.2, to calibrate the regression model. Those predictor variables selected to calibrate the SDSM for this study are presented in Table 4.1.

Table 4.1 Selected predictor variables for model calibration (defined previously in Table 3.2)

PREC		TMAX		TMIN	
NRA50	ERA40	NRA50	ERA40	NRA50	ERA40
r500	p__v	p8_v	p__v	p5_v	mlsp
s500	p8_v	rhum	r850	s850	s850
s850	r500	s850	s850	shum	shum
	s500	shum	shum	shum lag-1 ^b	temp
		temp	temp	temp	temp lag-1 ^b

^b Denotes predictor variable lagged by one

The results of the NRA50 and ERA40 regression model calibrations expressed in percentage of explained variance (R^2) and standard error (SE) for each predictand are presented in Table 4.2. For the NRA50 calibrated model, 15% of the daily PREC variance was explained by global-forcing for the NRA50 calibrated model compared to 21% for the ERA40 calibrated model. For daily TMAX and TMIN, approximately 60% and 64% of the variance in the maximum and minimum temperature can be explained by global-scale (predictor) forcing for the NRA50 calibration in comparison to 75% and 81% respectively for the ERA40 calibration. These results initially suggest that the ERA40 predictors related better to the predictands (PREC, TMAX and TMIN) at the Brantford MOE location than the NRA40. Furthermore, the ERA40 predictors generated less SE than those provided by the NRA50 when calibrating the model.

Table 4.2 Overall regression results of the SDSM model calibration produced by the NRA50 and ERA40 predictors for daily PREC, TMAX and TMIN.

	PREC		TMAX		TMIN	
	NRA50	ERA40	NRA50	ERA40	NRA50	ERA40
R^2	0.151	0.212	0.604	0.743	0.638	0.810
SE	0.458mm	0.438mm	2.903°C	2.094°C	3.169°C	2.510°C

However, the selection of appropriate predictors to calibrate the regression models remains a subjective step within the SDSM procedure. Currently, there are no rules or quantified thresholds set to decide whether a particular predictor is accepted or rejected. Another user may have selected a different suite of predictors based on more or less stringent criteria, likely producing different results from those of this study. Each user attempting to calibrate the SDSM incorporates their own personal understanding of how the predictand and predictors physically relate to one another and how important maintaining these relationships are within the calibration of the SDSM. However, similar R^2 and SE values were obtained from the calibration procedure by Wilby *et al.* (2002) for Toronto, Ontario, suggesting that the choice of predictors for PREC, TMAX and TMIN was sufficient for each reanalysis. Furthermore, Wilby *et al.* (2002) stated that obtaining relatively low R^2 values (<40%) for conditional variables such as PREC is not unusual. Gagnon *et al.* (2005) also noted low R^2 values (<40%) for PREC when calibrating the SDSM for three river basins in Québec. However, it is not possible to determine an exact threshold of significance in terms of R^2 values for predictor selection since the predictive ability of the SDSM varies geographically (Wilby *et al.*, 2002).

To further assess the choice of predictors, the synthesis of a 1975-1990 daily time-series was undertaken to validate the calibration of the NRA50 and ERA40 derived models (Figure 4.1). The validation differences between observed and downscaled PREC, TMAX and TMIN for both calibrated models were quantified in terms of RMSE and R^2 (Table 4.3 and 4.4). The validation results for the downscaled PREC values indicated that predictors obtained from both the NRA50 and ERA40 poorly reproduced the observed PREC values. Figure 4.1 (a) demonstrates that the NRA50 calibrated model

generally under-predicted mean daily PREC whereas the ERA40 model over-predicted. Over-prediction in the ERA40 model was most notable in July and September for the NRA50 model and January, April and August. In terms of the validation RMSE values, neither the NRA50 nor ERA40 models appeared to out-perform the other in terms of downscaling PREC (Table 4.3). Similarly, the R^2 results indicated that the same number of months with statistically significant values were produced by the NRA50 and ERA40 with 95% confidence ($R^2 \geq 0.247$). Overall, both calibrated models performed weakly for accounting for explained variance of PREC, most notably during the spring and summer months (March to September).

Figure 4.1 NRA50 and ERA40 validation results for PREC (a), TMAX (b) and TMIN (c).

Table 4.3 Model validation results for mean PREC, TMAX and TMIN in terms of monthly RMSE (1976-1990).

Month	PREC (mm)		TMAX (deg. C)		TMIN (deg. C)	
	NRA50	ERA40	NRA50	ERA40	NRA50	ERA40
J	1.14	0.83	1.67	0.65	1.55	1.27
F	1.12	0.78	1.61	0.75	2.00	0.89
M	0.96	1.14	1.16	0.88	1.01	0.80
A	1.14	1.95	1.09	1.00	0.93	0.67
M	1.59	1.35	1.31	0.75	1.81	0.62
J	1.33	1.32	1.00	0.81	1.05	0.66
J	1.34	1.90	0.77	0.57	0.59	0.44
A	1.76	2.49	1.29	0.58	0.79	0.56
S	2.11	1.68	0.83	0.82	1.13	0.74
O	1.78	1.61	1.13	1.01	0.88	1.08
N	1.14	0.82	0.83	1.13	1.20	1.15
D	0.94	1.46	1.57	0.60	1.40	1.30

Table 4.4 Model validation results for mean PREC, TMAX and TMIN in terms of monthly R^2 (1976-1990).

Month	PREC		TMAX		TMIN	
	NRA50	ERA40	NRA50	ERA40	NRA50	ERA40
J	0.144	0.789	0.649	0.942	0.742	0.824
F	0.269	0.445	0.833	0.929	0.658	0.907
M	0.086	0.000	0.794	0.885	0.851	0.898
A	0.015	0.051	0.664	0.899	0.728	0.680
M	0.021	0.320	0.713	0.916	0.491	0.769
J	0.069	0.074	0.696	0.815	0.556	0.708
J	0.296	0.012	0.584	0.890	0.629	0.880
A	0.003	0.036	0.562	0.826	0.624	0.803
S	0.005	0.066	0.513	0.496	0.231	0.493
O	0.123	0.110	0.603	0.890	0.646	0.690
N	0.282	0.588	0.692	0.586	0.657	0.872
D	0.319	0.246	0.809	0.959	0.886	0.922

N.B. Bold values indicate those months that are statistically significant with 95% confidence (df = 14)

The validation values, shown for TMAX and TMIN in Figures 4.1(b) and (c), suggested that both the NRA50 and ERA40 predictors calibrated the downscaling models adequately. Although the TMAX and TMIN RMSE values in Table 4.3 are low, it was noted that the ERA40 model consistently produced lower errors in all months relative to the NRA50 model, except during November and April. The R^2 values indicated that both

NRA50 and ERA40 derived models adequately accounted for the variance in observed TMAX and TMIN where all months were statistically significant with 95% confidence ($R^2 \geq 0.247$), except one month (September) for the NRA50 derived TMIN (Table 4.4).

Overall, these initial calibration and validation results suggest that the NRA50 and ERA40 predictors calibrated the SDSM sufficiently when attempting to generate daily PREC, TMAX and TMIN scenarios for the Brantford MOE meteorological station.

4.2 Statistical Analysis of Downscaled Scenarios

To determine the reanalysis most appropriate for calibrating the SDSM for scenario generation, the NRA50 and ERA40 derived models were respectively used to downscale four GCM output datasets. The sensitivity of the SDSM calibration to the reanalysis products (NRA50 and ERA40) when downscaling for daily PREC, TMAX and TMIN was evaluated in terms of model errors and confidence intervals in the estimates of the downscaled means and variances using four GCM output datasets. However, exploratory data analyses were performed first to determine whether parametric or non-parametric statistical tests would be used to investigate these errors in means and variances.

4.2.1 Exploratory Data Analysis

The exploratory analysis plots constructed to determine the normality and presence of outliers for the observed PREC, TMAX and TMIN (1961-90) for the month of January are illustrated in Figure 4.2. The density plot and histogram plot for daily PREC illustrated that the distribution was severely skewed to the right and can be

considered not normally distributed. Due to the nature of daily PREC, the majority of days experience no rainfall causing the density plot and histogram to become severely skewed to the right. As for the daily TMAX and TMIN, the density plot and histogram appeared nearly normally distributed with few if any outliers unlike for PREC. The Autocorrelation function (ACF) plots for the daily PREC, TMAX and TMIN for the month of January (1961-90) are shown in Figure 4.3 illustrating any autocorrelation among data points up to a lag of 30 days. The ACF plot of PREC showed that no significant correlation was present between daily data points lagging for more than one day at the 95% confidence level. For daily TMAX and TMIN, the ACF plots indicated that significant serial correlation was present between data points up to a lag of 13 and eight days respectively at the 95% confidence level, then diminish as the number of lag days progressed.

The analysis for normality and serial-correlation illustrated in Figures 4.2 and 4.3 indicated that the daily PREC time-series was not normally distributed and showed no serial-correlation between data points. Both TMAX and TMIN daily time-series appeared nearly normal and showed significant correlation between data points. Based on these tests, non-parametric analyses were most appropriate for this study due violation of the assumption of normality (PREC) and serial independence (TMAX and TMIN) required for parametric testing.

Although only the exploratory data analysis for the month of January is shown, analyses of the other downscaled and observed daily PREC, TMAX and TMIN for the other months of the year exhibited similar conclusions.

Figure 4.2 Histogram and density plots of PREC (a), TMAX (b) and TMIN (c) for the month of January at the Brantford MOE meteorological station.

Figure 4.3 ACF plots of PREC (a), TMAX (b) and TMIN (c) for the month of January at the Brantford MOE meteorological station. Dashed lines represent 95% confidence limits.

4.2.2 Error in Estimates of Means

To illustrate the difference between the observed and downscaled (NRA50 and ERA40) estimates of mean daily PREC, TMAX and TMIN for each month, the model errors and associated uncertainty (95% confidence intervals) are displayed in Figure 4.4, 4.5, 4.6 and 4.7 for each of the four GCMs. The errors between the mean daily observed and downscaled PREC, TMAX and TMIN for each month were tested using the non-parametric Wilcoxon Rank-Sum test with 95% confidence (Table 4.5). For mean daily PREC, Figures 4.4, 4.5, 4.6 and 4.7 (a) indicated that both calibrated models over-predicted mean daily PREC for the most months. However, the NRA50 calibrated model generally had the least error with respect to the observed PREC than the ERA40 based on the graphical comparison. Furthermore, the ERA40 model significantly over-predicted mean daily PREC for several months, whereas the NRA50 model simulated mean daily PREC more consistently, except for the month of October. The Wilcoxon test results (Table 4.5) however show that both the NRA50 and ERA40 calibrated model errors are insignificant in most months in terms of hypothesis testing ($p > 0.05$). More specifically, the mean daily PREC only failed to be reproduced by NRA50 calibrated models from the BCCR and CNRM GCM data in November and in October from the CCCMA and MPI GCM data. As for the ERA40 model only the months of April and July failed to be downscaled for the BCCR and CCCMA scenarios respectively, where the CNRM and MPI GCM data estimated mean daily PREC for all 12 months. Overall, both NRA50 and ERA40 calibrated models estimated the observed mean daily PREC adequately, showing no indication to which reanalysis would be a more appropriated choice for SDSM calibration.

Figure 4.4 Comparative (left) and model error (right) plots for the BCCR downscaled mean daily PREC (a), TMAX (b) and TMIN (c). Dashed lines (observed) and error bars (NRA50 and ERA40) indicate the monthly 95% confidence intervals.

Figure 4.5 Comparative (left) and model error (right) plots for the CCCMA downscaled mean daily PREC (a), TMAX (b) and TMIN (c). Dashed lines (observed) and error bars (NRA50 and ERA40) indicate the monthly 95% confidence intervals.

Figure 4.6 Comparative (left) and model error (right) plots for the CNRM downscaled mean daily PREC (a), TMAX (b) and TMIN (c). Dashed lines (observed) and error bars (NRA50 and ERA40) indicate the monthly 95% confidence intervals.

Figure 4.7 Comparative (left) and model error (right) plots for the MPI downscaled mean daily PREC (a), TMAX (b) and TMIN (c). Dashed lines (observed) and error bars (NRA50 and ERA40) indicate the monthly 95% confidence intervals.

Table 4.5 Results of the Wilcoxon Rank-Sum analysis (*p*-values) for differences of means of observed and downscaled daily PREC (a), TMAX (b) and TMIN (c) at the 95% confidence level.

(a)	GCM	BCCR		CCCMA		CNRM		MPI	
		<i>p</i> -values		<i>p</i> -values		<i>p</i> -values		<i>p</i> -values	
		NRA50	ERA40	NRA50	ERA40	NRA50	ERA40	NRA50	ERA40
	J	0.430	0.326	0.079	0.372	0.146	0.086	0.769	0.107
	F	0.607	0.164	0.657	0.484	0.699	0.317	0.126	0.529
	M	0.755	0.354	0.818	0.052	0.925	0.330	0.414	0.141
	A	0.445	0.041	0.817	0.654	0.245	0.081	0.992	0.124
	M	0.273	0.385	0.972	0.840	0.377	0.410	0.976	0.773
	J	0.174	0.386	0.219	0.713	0.898	0.065	0.777	0.380
	J	0.770	0.789	0.371	0.013	0.145	0.653	0.070	0.564
	A	0.402	0.429	0.119	0.114	0.217	0.786	0.115	0.476
	S	0.734	0.442	0.148	0.203	0.262	0.069	0.784	0.547
	O	0.205	0.669	0.002	0.118	0.165	0.954	0.023	0.122
	N	0.004	0.468	0.059	0.901	0.015	0.965	0.104	0.948
	D	0.960	0.085	0.419	0.219	0.418	0.752	0.578	0.846

(b)	GCM	BCCR		CCCMA		CNRM		MPI	
		<i>p</i> -values		<i>p</i> -values		<i>p</i> -values		<i>p</i> -values	
		NRA50	ERA40	NRA50	ERA40	NRA50	ERA40	NRA50	ERA40
	J	0.170	0.791	0.148	0.258	0.231	0.696	0.369	0.884
	F	0.320	0.841	0.568	0.475	0.761	0.668	0.222	0.786
	M	0.077	0.998	0.419	0.677	0.121	0.331	0.608	0.048
	A	0.319	0.529	0.174	0.401	0.251	0.431	0.498	0.746
	M	0.240	0.656	0.270	0.138	0.212	0.163	0.066	0.469
	J	0.129	0.151	0.168	0.054	0.270	0.145	0.052	0.135
	J	0.590	0.159	0.758	0.041	0.728	0.189	0.416	0.167
	A	0.016	0.511	0.105	0.341	0.132	0.769	0.902	0.457
	S	0.971	0.914	0.687	0.571	0.956	0.648	0.746	0.456
	O	0.729	0.065	0.158	0.010	0.581	0.048	0.278	0.075
	N	0.115	0.361	0.028	0.067	0.175	0.066	0.183	0.120
	D	0.643	0.530	0.839	0.445	0.701	0.057	0.741	0.220

(c)	GCM	BCCR		CCCMA		CNRM		MPI	
		<i>p</i> -values		<i>p</i> -values		<i>p</i> -values		<i>p</i> -values	
		NRA50	ERA40	NRA50	ERA40	NRA50	ERA40	NRA50	ERA40
	J	0.125	0.520	0.065	0.905	0.269	0.790	0.234	0.108
	F	0.438	0.390	0.298	0.753	0.109	0.652	0.439	0.290
	M	0.718	0.816	0.981	0.630	0.543	0.422	0.759	0.212
	A	0.166	0.844	0.675	0.870	0.566	0.343	0.009	0.275
	M	0.042	0.999	0.020	0.348	0.171	0.760	0.001	0.641
	J	0.559	0.354	0.969	0.121	0.953	0.312	0.586	0.764
	J	0.208	0.539	0.756	0.466	0.729	0.388	0.788	0.559
	A	0.685	0.898	0.787	0.963	0.731	0.954	0.539	0.953
	S	0.960	0.217	0.813	0.197	0.524	0.234	0.940	0.085
	O	0.322	0.172	0.499	0.068	0.320	0.058	0.619	0.002
	N	0.340	0.049	0.672	0.017	0.493	0.019	0.181	0.006
	D	0.458	0.837	0.323	0.364	0.245	0.319	0.357	0.008

N.B. Bold values indicate those months with significant difference in means

The downscaled daily TMAX and TMIN means, Figure 4.4, 4.5, 4.6 and 4.7 (b) and (c) respectively show very little difference in performance between the NRA50 and ERA40 calibrated models for each month where both model biases were relatively low (within $\pm 1^{\circ}\text{C}$). Similarly in terms of hypothesis testing, the Wilcoxon analysis (Table 4.5) indicated very few significant differences in the mean daily TMAX and TMIN ($p < 0.05$) between the observed and downscaled (NRA50 and ERA40). The NRA50 model respectively failed only to estimate the mean daily TMAX for August and November for the BCCR and CCCMA scenario, and for all 12 months from the CNRM and MPI data. For the ERA40 model, only the BCCR data reproduced the mean of all 12 months, the CCCMA failed for July and October, CNRM for October and MPI for March. As for the estimates of mean daily TMIN, the NRA50 and ERA40 models failed for the months May and November respectively for the BCCR and CCCMA scenarios. The NRA50 model downscaled no significant differences in means for all 12 months and for only one month (November) using the ERA40 model for the CNRM scenario. Finally, the most months with significant differences in means were observed using the MPI GCM data for both the NRA50 (April and May) and ERA40 (October, November and December) models. In general, both calibrated models estimated the observed mean daily TMAX and TMIN adequately similar to mean daily PREC, showing no indication to which reanalysis would be a more appropriated choice for SDSM calibration.

4.2.3 Error in Estimates of Variances

To illustrate the difference between the observed and downscaled estimates of variance for daily PREC, TMAX and TMIN, the NRA50 and ERA40 model errors and

associated uncertainty (95% confidence intervals) for the four GCMs are displayed in Figure 4.8, 4.9, 4.10 and 4.11. The differences between the mean daily observed and downscaled PREC, TMAX and TMIN for each month were tested using the non-parametric Levene test at the 95% confidence level (Table 4.6). For the variance of daily PREC, Figure 4.8, 4.9, 4.10 and 4.11 (a) demonstrated that both the NRA50 and ERA40 calibrated models struggled to closely reproduce the observed for most months based on the graphical comparisons for all GCMs. However, overall the NRA50 model did represent the variability of the observed data better than the ERA40, other than for the month of October. The ERA40 model consistently over-predicted the observed variability for most months of the year, except for June, September and November for all four GCMs. The Levene test results (Table 4.6) showed that for all the GCMs, the NRA50 model reproduced the observed variability for more months of the year than the ERA40 model. More specifically, the NRA50 failed to reproduce the variance of the observed daily PREC for four months using the BCCR output and three months using the other three GCM data. Using the ERA50 model, both the BCCR and CNRM data produced differences in variance for eight months, whereas the CCCMA and MPI data only produced five months with differences in variances. These results indicated that NRA50 was the most appropriate choice to calibrate the model for downscaling daily PREC in terms of variance, producing fewer months with statistically significant differences, most notably using the BCCR and CRNM scenarios.

Figure 4.8 Comparative (left) and model error (right) plots for the BCCR downscaled estimates of variances of PREC (a), TMAX (b) and TMIN (c). Dashed lines (observed) and error bars (NRA50 and ERA40) indicate the monthly 95% confidence intervals.

Figure 4.9 Comparative (left) and model error (right) plots for the CCCMA downscaled estimates of variances of PREC (a), TMAX (b) and TMIN (c). Dashed lines (observed) and error bars (NRA50 and ERA40) indicate the monthly 95% confidence intervals.

Figure 4.10 Comparative (left) and model error (right) plots for the CNRM downscaled estimates of variances of PREC (a), TMAX (b) and TMIN (c). Dashed lines (observed) and error bars (NRA50 and ERA40) indicate the monthly 95% confidence intervals.

Figure 4.11 Comparative (left) and model error (right) plots for the MPI downscaled estimates of variances of PREC (a), TMAX (b) and TMIN (c). Dashed lines (observed) and error bars (NRA50 and ERA40) indicate the monthly 95% confidence intervals.

Table 4.6 Results of the Levene analysis (*p*-values) for differences of means of observed and downscaled daily PREC (a), TMAX (b) and TMIN (c) at the 95% confidence level.

(a)	GCM	BCCR		CCCMA		CNRM		MPI	
		<i>p</i> -values		<i>p</i> -values		<i>p</i> -values		<i>p</i> -values	
		NRA50	ERA40	NRA50	ERA40	NRA50	ERA40	NRA50	ERA40
	J	0.002	0.000	0.006	0.009	0.000	0.001	0.016	0.001
	F	0.176	0.042	0.879	0.263	0.083	0.015	0.145	0.104
	M	0.230	0.004	0.055	0.000	0.113	0.031	0.206	0.005
	A	0.865	0.000	0.080	0.000	0.042	0.000	0.136	0.000
	M	0.946	0.015	0.076	0.232	0.589	0.129	0.074	0.079
	J	0.980	0.524	0.474	0.182	0.280	0.057	0.190	0.260
	J	0.186	0.108	0.618	0.871	0.477	0.020	0.854	0.333
	A	0.022	0.016	0.862	0.010	0.239	0.000	0.452	0.001
	S	0.797	0.952	0.759	0.966	0.527	0.331	0.592	0.724
	O	0.000	0.007	0.002	0.253	0.002	0.009	0.005	0.357
	N	0.707	0.260	0.031	0.079	0.647	0.125	0.754	0.091
	D	0.026	0.007	0.188	0.003	0.070	0.005	0.034	0.028

(b)	GCM	BCCR		CCCMA		CNRM		MPI	
		<i>p</i> -values		<i>p</i> -values		<i>p</i> -values		<i>p</i> -values	
		NRA50	ERA40	NRA50	ERA40	NRA50	ERA40	NRA50	ERA40
	J	0.000	0.292	0.000	0.004	0.000	0.040	0.000	0.072
	F	0.000	0.441	0.000	0.014	0.000	0.005	0.000	0.039
	M	0.000	0.543	0.001	0.220	0.000	0.078	0.004	0.107
	A	0.000	0.003	0.000	0.592	0.000	0.814	0.000	0.654
	M	0.000	0.725	0.000	0.058	0.000	0.280	0.000	0.168
	J	0.000	0.006	0.000	0.860	0.000	0.951	0.000	0.274
	J	0.459	0.028	0.413	0.560	0.043	0.042	0.000	0.918
	A	0.191	0.000	0.747	0.014	0.000	0.291	0.000	0.025
	S	0.000	0.000	0.000	0.492	0.000	0.959	0.000	0.649
	O	0.000	0.048	0.000	0.000	0.000	0.000	0.000	0.000
	N	0.000	0.051	0.000	0.001	0.000	0.015	0.000	0.012
	D	0.000	0.349	0.000	0.309	0.000	0.456	0.000	0.791

(c)	GCM	BCCR		CCCMA		CNRM		MPI	
		<i>p</i> -values		<i>p</i> -values		<i>p</i> -values		<i>p</i> -values	
		NRA50	ERA40	NRA50	ERA40	NRA50	ERA40	NRA50	ERA40
	J	0.031	0.368	0.809	0.040	0.029	0.189	0.000	0.030
	F	0.000	0.170	0.642	0.664	0.000	0.148	0.009	0.097
	M	0.003	0.612	0.836	0.370	0.040	0.762	0.110	0.671
	A	0.000	0.996	0.000	0.405	0.000	0.502	0.029	0.456
	M	0.001	0.612	0.000	0.667	0.000	0.686	0.039	0.000
	J	0.013	0.089	0.000	0.794	0.000	0.780	0.036	0.000
	J	0.312	0.002	0.012	0.155	0.785	0.501	0.350	0.000
	A	0.044	0.019	0.001	0.060	0.022	0.012	0.567	0.000
	S	0.888	0.524	0.049	0.599	0.579	0.407	0.256	0.000
	O	0.005	0.643	0.000	0.903	0.000	0.382	0.310	0.000
	N	0.008	0.932	0.000	0.430	0.016	0.741	0.539	0.000
	D	0.071	0.653	0.319	0.578	0.054	0.594	0.002	0.003

N.B. Bold values indicate those months with significant difference in

The downscaled variances of daily TMAX plotted in Figure 4.8, 4.9, 4.10 and 4.11 (b) indicated the ERA40 model consistently reproduced the variance of the observed data for most months, whereas the NRA50 model only represented the observed variability closely from June to August across all GCMs. The test for equality of variance at the 95% confidence level (Table 4.6) also indicated that the ERA40 model closely downscaled the observed variance ($p>0.05$) for several months outperforming the NRA50 model. Both the BCCR and CCCMA failed to reproduce observed variance using the NRA50 model, except for the months of June and August. For the CNRM and MPI data, the NRA50 failed for all 12 months to estimate the observed variance of daily TMAX. Using the ERA40 model, six months were successfully reproduced from the BCCR as well as seven months for the CCCMA and CNRM respectively. The MPI data showed only 4 months with significant differences in estimates variances using the ERA40 model. Overall, the results suggested that ERA40 reanalysis was the most appropriate choice for estimating variances of observed TMAX producing fewer months with significant difference, most notably for the MPI scenario.

The comparative plots illustrated in Figure 4.8, 4.9, 4.10 and 4.11 (c) for the downscaled variability of daily TMIN indicated that the ERA40 model more closely simulated the variability of the observed data than the NRA50 model. Generally, the NRA50 model poorly represented the observed variance for most months between April and November in comparison to the ERA40 model, except for the MPI scenario. Similarly, the Levene test results for TMIN at the 95% confidence level indicated that the ERA40 modelled observed variability overall better than the NRA50 model, except for the MPI scenario (Table 4.6). As for the BCCR and CNRM scenarios, the NRA50 model

poorly reproduced the variance of daily TMIN for nine months where as the ERA40 model successfully simulated the variance for 10 and 11 months respectively. Similarly, the NRA50 model failed to reproduce observed variance for eight months of the year where the ERA40 only failed in the month of January. The MPI was the only GCM scenario to suggest that the NRA50 out-performed the ERA40 model in terms of estimating observed variances for TMIN indicating only six months in comparison to nine months with significant differences. Similar to TMAX, the results suggested that ERA40 reanalysis was the most appropriate choice for estimating variances of observed TMIN producing fewer months with significant difference, except for the MPI generated scenario.

4.2.4 Discussion of Downscaled Scenarios

These results indicate that the commonly used NCEP/NCAR reanalysis (i.e.NRA50) is the most appropriate choice for calibrating the SDSM for downscaling daily PREC. However, the ERA40 derived model produced better agreement for downscaling daily TMAX and TMIN for the Brantford MOE meteorological station. Users less specialized in the climate change community have been looking to the literature to determine the appropriate method of downscaling PREC, TMAX and TMIN for climate change studies. Currently, the NCEP/NCAR reanalysis (i.e. NRA50) is the only suite of predictors being used throughout the literature to calibrate the SDSM for a variety of climate change studies. When attempting to reproduce the observed means or variances either the NRA50 or ERA40 reanalysis may be the better choice for model calibration depending on the downscaling location. The skill of the SDSM varies

geographically due to the heterogeneous nature of a predictand within an area, such as daily precipitation (PREC), as the relationships between predictands and predictors are established specifically for one location. The choice of reanalysis to calibrate the SDSM may also depend on the months or seasons of interest to the user as the regression models are built separately for each month of the year. Although a reanalysis may outperform another for most months of the year, those months may not be of interest or importance for certain applications. Furthermore, the fundamental predictand/predictor relationship established by the reanalysis during calibration may be different between the predictand and the GCM predictors used to generate the scenarios. Therefore, an SDSM user must determine whether the commonly used NCEP/NCAR or other reanalysis products are most appropriate for the context of their study considering the geographic location, months of interests and GCM selected to generate downscaled scenarios.

4.3 Hydrologic Application

To assess the impact of reanalysis choice in hydrologic simulations, the downscaled PREC, TMAX and TMIN produced from the four GCM datasets were used as inputs into the SWAT model to simulate daily runoff. Before the results of this analysis are discussed, the basic statistics and overall predictive ability of the hydrologic model will be assessed using observed PREC, TMAX and TMIN data. Subsequently, the impact of reanalysis choice in hydrologic modelling will be assessed in terms of estimates of means and variances of daily discharge for the four GCM scenarios.

4.3.1 SWAT Simulation Using Observed Data

To illustrate the performance of the SWAT model using observed 1965-1990 inputs to for the Fairchild Creek watershed, the simulated streamflow and associated uncertainty (95% confidence intervals) are illustrated in Figure 4.12. The errors between mean daily observed and simulated discharge for each month were tested in terms of RB, RMSE and RMAE as well as explained variance in terms of R^2 (Table 4.7).

Figure 4.12 Observed and simulated streamflow using observed climatic inputs for Fairchild Creek watershed. Dashed lines (observed) and error bars (simulated) indicate the monthly 95% confidence intervals.

Figure 4.12 illustrates that the mean daily discharge produced by the observed climatic inputs agreed well with the observed streamflow for the months January to May and November, consistently overestimated the observed streamflow for the months July to October, and underestimated for the month of December. The RB, RMSE and RMAE also indicated that the SWAT model produced the lowest model error in the months of January to May and November in comparison to the months of July to October and

December. The SWAT model simulated statistically significant R^2 values for all months with 95% confidence ($R^2 \geq 0.151$), except for July and October. However, the R^2 values appeared relatively low for the most months except February and May indicating that the SWAT model simulation may not consistently reproduce the variance of the observed streamflow.

Table 4.7 Monthly statistics for observed and simulated streamflow for Fairchild Creek watershed using observed climatic inputs (1965-1990).

Month	RB	RMSE (cms)	RMAE	R^2
J	-0.20	1.67	0.43	0.587
F	-0.24	2.45	0.30	0.759
M	-0.10	3.94	0.29	0.342
A	-0.19	3.22	0.32	0.323
M	0.29	1.52	0.39	0.726
J	1.36	2.58	1.36	0.614
J	2.46	3.04	2.46	0.002
A	2.51	2.81	2.56	0.495
S	1.97	2.64	1.97	0.542
O	0.51	2.11	0.94	0.029
N	0.03	1.54	0.38	0.545
D	-0.32	2.79	0.46	0.399

N.B. Bold values indicate those months that are statistically significant with 95% confidence (df = 24)

The over-predicted streamflow errors noted in the Figure 4.12 and in Table 4.7 for the months from July to October may have been attributed to the setup and calibration provided by Bonnycastle (2006) that did not include the wetland areas of the Fairchild Creek watershed into the SWAT model. Andres *et al.* (1989) stated that wetlands act as significant reservoirs for surface runoff especially if disconnected from the drainage network, accounting for the higher simulated runoff during warmer months. Conversely during the colder months, wetlands usually become frozen causing much higher overland flow to the drainage system and may be responsible for the under-predicted streamflow errors in January to April and November between the simulated and observed daily

discharge noted in Figure 4.12 and in Table 4.7. Thus for consistency, the streamflow simulated from the observed inputs were used as the comparative analogue for the subsequent NRA50 and ERA40 simulations, rather than the observed streamflow obtained from the “Fairchild Creek near Brantford” flow gauge. This comparative analogue produced by the observed climatic inputs will be referred to in the following sections as the “baseline” streamflow.

4.3.2 SWAT Simulations Using Downscaled Scenarios

The mean daily discharge simulated by the downscaled (NRA50 and ERA40) climatic inputs as well as the association uncertainty (95% confidence intervals) are illustrated in Figure 4.13 and the errors in estimates of means determined using the Wilcoxon Rank-Sum are presented in Table 4.8. The mean daily discharge simulated for all four GCM suggested that the ERA40 input variables consistently over-predicted the baseline streamflow, most notably during the month the peak month of March. Similarly, the NRA50 model consistently over-predicted baseline mean daily discharge for most months and during the peak month (March) for all GCMs. In contrast, the NRA50 climatic inputs produced less bias and more overall agreement to the mean daily discharge for all months but October. The Wilcoxon test for differences in means (Table 4.8) illustrated that both the NRA50 and ERA40 model simulations failed to reproduce the baseline mean daily discharge ($p < 0.05$) for most months of the year. More specifically, the NRA50 BCCR and CNRM climatic inputs simulated eight and ten respective months with significant differences in means where as the CCCMA and MPI only simulated significant difference for five and six months respectively. On the other

Figure 4.13 Baseline and simulated estimates of means of streamflow using downscaled climatic inputs for Fairchild Creek watershed (BCCR (a), CCCMA(b), CNRM(c) and MPI(d)). Dashed lines (observed) and error bars (downscaled) indicate the monthly 95% confidence intervals.

Table 4.8 Results of the Wilcoxon Rank-Sum analysis (p-values) for differences of means of baseline and simulated daily discharge at the 95% confidence level.

GCM	BCCR		CCCMA		CNRM		MPI	
	<i>p</i> -values		<i>p</i> -values		<i>p</i> -values		<i>p</i> -values	
Month	NRA50	ERA40	NRA50	ERA40	NRA50	ERA40	NRA50	ERA40
J	0.000	0.000	0.053	0.000	0.000	0.000	0.394	0.000
F	0.000	0.000	0.095	0.000	0.000	0.000	0.643	0.000
M	0.000	0.000	0.003	0.000	0.000	0.000	0.000	0.000
A	0.204	0.000	0.175	0.000	0.000	0.000	0.000	0.000
M	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
J	0.638	0.000	0.000	0.000	0.000	0.000	0.000	0.000
J	0.132	0.000	0.488	0.000	0.018	0.000	0.000	0.000
A	0.014	0.000	0.093	0.000	0.037	0.000	0.935	0.000
S	0.004	0.000	0.061	0.922	0.043	0.000	0.662	0.000
O	0.021	0.005	0.003	0.012	0.052	0.000	0.213	0.368
N	0.683	0.065	0.000	0.732	0.297	0.000	0.145	0.011
D	0.000	0.000	0.123	0.000	0.001	0.000	0.008	0.000

N.B. Bold values indicate those months with significant difference in means

hand, the ERA40 model failed to reproduce the mean daily discharge produced by the observed climatic inputs for all but a few months. Furthermore, for all GCM scenarios both calibrated models produced significant differences in mean daily discharge for the peak month of March. Although the overall results are not ideal, the statistical analysis did indicate that the climatic inputs generated from the NRA50 model would be the most appropriate choice for simulating mean daily discharge, most notably for the CCCMA and MPI scenarios.

The errors and associated uncertainty (i.e. 95% confidence intervals) in the estimates of daily streamflow variance are illustrated in Figure 4.14. Also, analysis of variance was performed using the Levene test using the baseline and simulated streamflow produced from the NRA50 and ERA40 climatic inputs Table 4.9. Overall both models over-predicted the variance of daily discharge, most notably in March (all GCMs). Additionally, the NRA50 derived inputs notably struggled to produce the variance of daily streamflow in August using the CNRM whereas the ERA40 derived inputs struggled in April (CCCMA and MPI), July (CNRM) and August (BCCR and MPI). Similar to the estimates of means, the NRA50 model produced less bias and more overall agreement to the variance produced by the observed than the ERA40 model for most months. As for the Levene test for all GCMs (Table 4.9), both the NRA50 and ERA40 models produced climatic inputs simulating significant differences in variance for several months. More specifically, the ERA40 model climatic inputs failed to reproduce the observed variance for eight months whereas the NRA50 model only produced six months for the BCCR scenario. However, in the case of the CCCMA, CNRM and MPI scenarios, the NRA50 inputs only produced three months with significant differences in

Figure 4.14 Baseline and simulated estimates of variance of streamflow using downscaled climatic inputs for Fairchild Creek watershed (BCCR (a), CCCMA(b), CNRM(c) and MPI(d)). Dashed lines (observed) and error bars (downscaled) indicate the monthly 95% confidence intervals.

Table 4.9 Results of the Levene analysis (p-values) for differences of variance of baseline and simulated daily discharge at the 95% confidence level.

GCM	BCCR		CCCMA		CNRM		MPI	
	<i>p</i> -values		<i>p</i> -values		<i>p</i> -values		<i>p</i> -values	
Month	NRA50	ERA40	NRA50	ERA40	NRA50	ERA40	NRA50	ERA40
J	0.068	0.205	0.032	0.030	0.510	0.204	0.420	0.133
F	0.585	0.041	0.229	0.459	0.398	0.436	0.176	0.036
M	0.006	0.001	0.056	0.002	0.000	0.000	0.005	0.000
A	0.691	0.000	0.110	0.000	0.506	0.002	0.000	0.000
M	0.812	0.018	0.185	0.703	0.645	0.088	0.051	0.047
J	0.675	0.803	0.571	0.216	0.255	0.085	0.124	0.109
J	0.042	0.015	0.893	0.087	0.040	0.004	0.174	0.033
A	0.003	0.004	0.630	0.004	0.061	0.000	0.344	0.000
S	0.960	0.621	0.891	0.590	0.488	0.703	0.652	0.611
O	0.000	0.004	0.001	0.182	0.001	0.008	0.001	0.123
N	0.271	0.068	0.012	0.032	0.776	0.016	0.195	0.053
D	0.009	0.004	0.296	0.001	0.063	0.003	0.711	0.107

N.B. Bold values indicate those months with significant difference in variances

streamflow variance. In contrast, the climatic inputs derived from the ERA40 model produced significant differences in variance for six months using the CCCMA and MPI scenarios and for seven months using the CNRM scenario. Furthermore, the estimates of variance for the peak streamflow month of March failed to be consistently reproduced by both the NRA50 and ERA40 climatic inputs. These results indicate that NRA50 was the most appropriate choice to calibrate the model for producing climatic inputs for simulating the variance of daily discharge, most notably using the CCCMA, CRNM and MPI scenarios.

4.3.3 SWAT Downscaled Simulation Discussion

When downscaling the four GCMs, the NRA50 model more closely simulated the means and variance of the streamflow for the Fairchild Creek watershed. In the previous sub-section 4.2, it was noted that the NRA50 model more closely reproduced the means and variances of the observed daily PREC whereas ERA40 model more closely reproduced observed daily TMAX and TMIN. Although daily TMAX and TMIN are used as climatic inputs into the SWAT model, the daily PREC input is the most significant input to simulate streamflow from the rainfall-runoff model and thus was reproduced best by the NRA50 model. While this analysis has demonstrated that the NRA50 derived climatic inputs weakly reproduce means of daily streamflow, the variances for several months were reproduced sufficiently. Thus in the case of NRA50 simulations, the streamflow could be bias-corrected to adjust for the consistent over-prediction and differences in the mean daily streamflow to retain the equality of the variances.

The comparison plots and statistical analyses indicated that both the calibrated models over-predicted and simulated significantly different peak flows particularly during the month of March in terms of mean and variance. In the context of hydrologic modelling, these peak freshet flows in March need to be accurately simulated by the NRA50 and ERA40 models to determine appropriate river management practices for mitigating future climate change impacts.

These analysis of means and variances of the simulated daily discharge for the time-series 1965-1990 indicate that there are significant implications to the reanalysis (NRA50 vs. ERA40) used to calibrate the SDSM and produce future climatic inputs for hydrologic prediction. In the context of this research, users from the broader, less specialized climate change community attempting to predict the future hydrologic regimes of a region from downscaled output must be aware of the importance of this choice. SDSM users have been looking to the literature to determine the appropriate method of downscaling PREC, TMAX and TMIN for a variety of climate change studies and will calibrate the SDSM with the commonly NCEP/NCAR reanalysis products. Although this study did indicate that the NCEP/NCAR NRA50 calibrated model did reproduce the simulated streamflow in terms of estimated means and variances better than the ECMWF ERA40 calibrated model for the Fairchild Creek watershed, this may not be the case for other regions, applications or GCM selected to downscale. Studies undertaken by Wilby and Dettinger (2000) in California and Diaz-Nieto and Wilby (2005) in the United Kingdom noted that downscaled climatic inputs supplied by an NCEP/NCAR calibrated SDSM coupled with a hydrologic model adequately simulated overall mean daily streamflow. However, these studies failed to investigate other choices

of reanalyses for calibrating SDSM that may have produced more accurate climatic input for the simulation of daily streamflow. Accordingly, Gagnon *et al.* (2005) noted that the NCEP/NCAR derived inputs did not produce adequate estimates of mean daily streamflow as well as magnitude or timing of the freshet within three basins in Québec. Thus, SDSM users should be aware that the NCEP/NCAR reanalysis products will not necessarily be the most appropriate choice for calibrating the SDSM. Other reanalysis products should be investigated in the context of the application to ensure the most suitable reanalysis product is selected for predicting accurate future climatic variables.

CHAPTER 5: SUMMARY AND CONCLUSIONS

Climate centres have developed GCMs in an attempt to predict future climatic trends for numerous forecasting and impact studies. However, the remaining issue with the use of GCMs for various local applications is the coarse spatial resolution of the output dataset. To better resolve this GCM scaling issue, many approaches have been designed in the past decade to downscale GCM output data to predict future regional climatic variables, such as temperature and precipitation. The Statistical DownScaling Model (SDSM) has been identified as one of the leading statistical downscaling techniques and is currently recommended by the Canadian Climate Impacts and Scenarios (CCIS, 2007) as an appropriate downscaling model. The SDSM statistically identifies relationships between large-scale *predictors* (i.e. GCM) and local-scale *predictands*, using a multiple linear regression model. Reanalyses, such as the NCEP/NCAR and ECMWF, are important components for the structuring of the SDSM, as they supply the predictor values for the calibration and validation of the model. It is well known that the reanalysis products contain biases which may subsequently impact the development of downscaling scenarios as well as any application using these scenarios as inputs. Throughout the literature, the NCEP/NCAR reanalysis products (i.e. NRA50) have been the only datasets used to calibrate the SDSM for downscaling GCMs output data. However, this study has shown that there may be more appropriate choices of reanalysis products used to calibrate the SDSM. Thus, this research aimed to assess the ability of the most current NCEP/NCAR (NRA50) and ECMWF (ERA40) reanalyses to calibrate the SDSM for regional climate forecasting. Through direct comparison between the model errors of the downscaled daily precipitation (PREC) and temperature

(TMAX and TMIN) for the Brantford MOE meteorological station, the results indicated that the NCEP/NCAR reanalysis may not be the most appropriate choice for SDSM calibration.

Initially, when calibrating and validating the SDSM with the respective reanalyses for downscaling daily PREC, TMAX and TMIN at the Brantford MOE meteorological station, the results indicated that overall the ERA50 produced fewer errors than the NRA40. However, the differences in errors between both calibrated model were quite similar and both reanalyses adequately calibrated the SDSM for downscaling PREC, TMAX and TMIN using the four various GCMs used in this study. Then using the NRA50 and ERA40 calibrated model to produce downscaled PREC, TMAX and TMIN scenarios from the GCM output datasets, it was found that for daily PREC the NRA50 calibrated model outperformed the ERA40 model in terms of reproducing means and variances. However, when attempting to downscale TMAX and TMIN at the same location, the ERA40 calibrated model reproduced the monthly means and variances of the observed data than the most often used NRA50 calibrated model.

A practical application of these PREC, TMAX and TMIN scenarios downscaled using the NCEP/NCAR and ECMWF calibrated models were assessed in a hydrologic modelling context using the SWAT calibrated for the Fairchild watershed within the Grand River Basin. It was noted when these downscaled variables were inputted into the SWAT hydrologic model, that the NRA50 model reproduced the means and variances of the Fairchild Creek watershed daily streamflow more accurately than the ERA40 model due to the sensitivity of the model to the daily PREC input. However, neither the NRA50 nor ERA40 model consistently reproduced the means and variances of during the month

of March during which the peak streamflow or freshet occurs in the Fairchild Creek watershed.

Overall, the results from this research indicated that when SDSM users attempt to downscale predictands, whether it is daily precipitation (PREC) or temperature (TMAX and TMIN) or other variables, they should consider reanalyses other than the NCEP/NCAR for the best model calibration possible. Additionally, the users should understand the implications of the choice of reanalysis as the coupling of the SDSM with other predictive models may propagate errors through the various processes. In southwestern Ontario, water managers, conservation authorities, city planners, public administrators, agricultural industry as well as other stakeholders, need to reassess present day policies and management practices regarding the use and allocation of water based on reliable downscaled climate data. When attempting to predict these climatic changes, users need to be aware that the NCEP/NCAR reanalysis used throughout the literature to calibrate the SDSM may not be the most appropriate choice for downscaling daily precipitation and temperature climatologies. This study has demonstrated that the NCEP/NCAR reanalysis out performed the ECMWF reanalysis in terms of SDSM calibration for producing of climatic variables for simulating daily discharge in the Fairchild Creek watershed. However, further comparison of the NCEP/NCAR and ECMWF calibrated models using a variety of other locations, GCM scenarios and applications will be needed to support this conclusion and improve the SDSM as predictive tools for local-scale climate change studies.

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